2015

A MEASURE OF SOCIAL BEHAVIOR IN TEAM-BASED, MULTIPLAYER ONLINE GAMES: THE SOCIALITY IN MULTIPLAYER ONLINE GAMES SCALE (SMOG)

Chelsea M. Hughes
Virginia Commonwealth University

A MEASURE OF SOCIAL BEHAVIOR IN TEAM-BASED, MULTIPLAYER ONLINE GAMES: THE SOCIALITY IN MULTIPLAYER ONLINE GAMES SCALE (SMOG)

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science at Virginia Commonwealth University

By: CHELSEA MARIE HUGHES
B.A., East Carolina University, 2013

Director: Everett L. Worthington, Jr., Ph.D.
Title: Professor and Director of Clinical Training
Department of Psychology

Virginia Commonwealth University
Richmond, Virginia
April 2015

Table of Contents

List of Tables

Abstract

A MEASURE OF SOCIAL BEHAVIOR IN TEAM-BASED, MULTIPLAYER ONLINE GAMES: THE SOCIALITY IN MULTIPLAYER ONLINE GAMES SCALE (SMOG)

Chelsea Marie Hughes, B.A.

A thesis submitted in partial fulfillment of the requirements for the degree of Master of Science at Virginia Commonwealth University

Virginia Commonwealth University, 2015

Major Director: Everett L. Worthington, Jr., Ph.D.
Professor and Director of Clinical Training
Department of Psychology

Video games have become a new platform for social interaction. I review the sociality of video games and the relationship between virtual- and real-world behaviors. I review and address the pros and cons of methods of measuring social behavior. Finally, I present two studies drawn from internet populations. In Study 1 (N = 250), I develop a scale, The Sociality in Multiplayer Online Games Scale (SMOG), which measures the frequency of social gaming behaviors in team-based, multiplayer online games. I hypothesized these to align on dominance and affiliation dimensions of social interaction (Kiesler, 1982). In Study 2 (N = 104), I conduct a confirmatory factor analysis, which supports a two-factor structure—Destructive and Constructive social behavior, resulting in the SMOG-6. I examine construct validity using measures of dominance and affiliation. Controlling for age, gender, and frequency of game-play, both factors predict dominance. SMOG-Destructive negatively, and SMOG-Constructive positively, predicted affiliation.

A Measure of Social Behavior in Team-Based, Multiplayer Online Games:
The Sociality in Multiplayer Online Games Scale (SMOG)

Psychologists have recently explored human interaction with video games (Li, Liau, & Khoo, 2013; Vorderer & Bryant, 2012). This research has taken a variety of approaches, from the relationship between video games and aggression (Hollingdale & Grietemeyer, 2013) to the multitude of benefits one can incur from playing video games (Granic, Lobel, & Engels, 2014). As entertainment technologies become more advanced, they have acquired new methods of influencing our lives. What was once merely a mechanism of entertainment has become a community-based subculture -- a multifaceted, world-wide platform for social interaction and personal growth (Granic, Lobel, & Engels, 2014).

Review and Statement of the Problem

Method of the review. In the following review of relevant literature, I review the scales, questionnaires, inventories and measures that assess social behavior in online games. Individual *PsycTESTS* searches in March 2015 for the terms "video game," "online game," "gaming," and "game" yielded 20 unique results. Six scales assessed problematic use and addiction. Four tests measured attitudes towards video games. Two tests assessed motivation for gaming. Another two tests measured specific behavioral factors (i.e., risk-taking and cheating). The remaining six measures examined constructs and topics including perceived sexism, engagement and enjoyment, frequency of play, self-efficacy, and non-video games.

Results of the review. Results of the review suggest that a scale measuring social behavior in online games has yet to be developed. Without such studies, I will instead summarize the empirical evidence relating to social interaction in online gaming. I will also review methods of measuring social behavior, identifying the pros and cons of each. Finally, I will discuss the overall status of the field and introduce the present study as it relates to the needs of the field.

Sociality of video games.

Gaming has a social component. Video games are platforms for social behavior (Caplan, 2003; Davis, Flett, & Besser, 2002). Every behavior involves an interaction, and each individual brings with him or her certain propensities to that interaction (Bowman, Weber, Tamborini, & Sherry, 2013). Many people may find have difficulty believing the complexity of social interaction in online gaming. After all, only three decades ago, games like Centipede and Pac-Man were the forerunners of the gaming scene. The sociality of these games was limited to spectatorship and competitive turn-taking. Multiplayer functionality did not exist, and social needs were met outside of the game itself. Yet video games have come a long way since then. Graphical capabilities have matured from a 680 x 400 pixel arcade-style machine to a 1248 x 1536 pixel device that can rest in the palm of your hand. User input has grown from buttons and a joystick to the endless combination of mouse clicks and a QWERTY keyboard. These advancements have creased a virtual reality where gamers can supplement, or even replace, their real-world social activity. In their non-refereed annual gaming research study, conducted by a third-party contactor, the Entertainment Software Association (ESA) found in a sample of over 2,200 nationally-representative households that 62% of gamers play games with others, either in-person or online (ESA, 2014). Some people actually prefer virtual interaction to real-world social interaction (Ng & Wiemerhastings, 2005).

Game features enhance social interaction. There are several features to modern video games that facilitate social interaction and immersion. Many video games feature a chat space where players can communicate with their allies and enemies. When such a space is not provided, online-communication software, like Skype and RaidCall, can be used. These features not only can enhance cooperation, but also create a sense of playing “alongside” teammates, likely creating a more humanized gaming experience. Gamers can also personalize their in-game characters. Many games offer the ability to personalize clothing, stature, and facial features of their online avatars, even so far as their scars, eye-color, and jawline (e.g., *The Sims, Mass Effect* series, etc.). These modifications may allow players to feel more “connected” with their characters, where instead of playing the game *utilizing* a character, gamers may play the game *as* their virtual-selves (Lewis, Weber, & Bowman, 2008).

Social behavior in video games: The “real” self and the “virtual” self. Some research has shown a strong positive relationship between people’s social behavior in the virtual world and the real world (Graham & Gosling, 2012; Greitemeyer & Cox, 2013; Ma, Li, & Pow, 2011). For example, in a survey of 1,040 World of Warcraft players, researchers Yee, Ducheneaut, and Nelson (2011) collected automated behavioral data reports (made publicly available by the game developers, Blizzard Games, but not refereed in a scientific forum) and self-reported measures of personality. They found that extroverted individuals preferred group activities versus solo activities in the virtual world. Furthermore, a variety of personality traits (like agreeableness, openness to experience, and emotional stability) accurately predicted virtual-world behaviors (like giving out positive emotes, avatar gender-choice, and number of characters the gamers play). These results suggest that personality influences both real-world and online social behaviors.

Computer-mediated interaction changes our behavior. Some research (e.g., Joinson, 1999; Kiesler et al., 1984) has suggested that computer-mediated communication provides many of the same conditions found in de-individuation-anonymity. Deindividuation theory suggests that a group reduces the sense of identity in its individuals, resulting in reduced self-awareness and reduced self-regulation. Joinson (1999, 2001) suggests that computers moderate behavior in a similar way. For example, Joinson (1999) studied self-reported measures of social desirability, self-esteem, and self-consciousness in 82 undergraduate students. Participants completed these measures either online (anonymously) or using pen and paper (where they were asked to write their names on their papers). Results indicated that participants who completed the survey anonymously reported higher self-esteem, and lower social-desirability and self-consciousness when compared to the nonanonymous survey. Later, Joinson (2001) studied levels of self-disclosure in computer-mediated communication in undergraduate students. In the first study (N = 40), he compared the amount of self-disclosure across two conditions: face-to-face interaction and computer-mediated, text-based interaction. In the second study (N = 42), he also examined self-disclosure, but across two different conditions: computer-mediated text-based interaction and computer-mediated video interaction. In both studies, he found that greater anonymity significantly predicted more self-disclosure. Without the personalization of their actions, people may be more willing to express themselves in socially unacceptable ways or to express ideas and sentiments that would otherwise remain hidden in face-to-face interaction—thus acting in ways different from their "real selves."

The effect of computer interaction on social behavior seems to contradict the consistency between the "virtual" self and "real-world" self. However, consider how anonymity translates to real-life. People behave differently when they are being watched (e.g., Hoffman, McCabe, & Smith, 1996). From children on a playground to adults in the workplace, people change their behavior based on whether they feel like someone is looking (Bateson, Nettle, & Roberts, 2006; Keller & Pfattheicher, 2011). Bandura (1999) attributes this change to his theory of moral disengagement. Moral disengagement theory posits that when people are in a position to dehumanize another individual, they are more likely to engage in less moral (or more immoral) actions than when people are more humanized; the same effect occurs when individuals can depersonalize their actions. This dehumanization of peers and depersonalization of actions is an inherent factor in the online gaming experience, particularly in competitive play. Rather than being recognized as people playing the game, other gamers can easily perceive their teammates and enemies as just a name, or an avatar.

That is not to say that all online gaming experiences are depersonalized or anonymous. This depends on a variety of factors, from information on a gamer's profile to how much a gamer feels "connected" with his or her avatar, or gamer-tag (i.e., their in-game name, often consistent across games). In a study of 124 active users of Second Life, a virtual world platform, Midha and Nandedkar (2012) found a strong relationship between perceived similarity between a user and his or her avatar, and the user's feelings of identification with that avatar. One might conclude that the more a gamer identifies with their in-game representation, the more personalized its actions become. According to the converse of Bandura's moral disengagement theory – what he has coined the "Power of Humanization" (p. 202)—this would result in more moral (and less immoral) behavior coming from that avatar, and thus from the user. Unfortunately, however, the intensely personalizing features in Second Life are not available in most massive multiplayer online games. Given the inherent anonymity and depersonalization of most online gaming activities, it should be no surprise that we see such a prevalence of anti-social, socially-undesirable behavior online.

Virtual-world behavior can affect our real-world behavior. Several studies have shown that virtual-world behaviors can have subsequent effects on our real-world behaviors (e.g., Grizzard et al., 2014; Whitaker & Bushman, 2014). For example, extensive research has shown the relationship between aggressive video-gaming and aggressive behavior (Hollingdale & Grietemeyer, 2013). While some studies have found evidence that trait aggression is the cause, not the consequence, of aggressive gaming (e.g., Kowert, Cogelgesand, Festl, & Quandt, 2015), others have found direct causation between aggressive gaming and subsequent aggressive behavior (e.g., Yang, Huesmann, & Bushman, 2014). Attributes of the avatar, like race and gender, can also moderate this causal relationship (Yang, Huesmann, & Bushman, 2014). In a sample of 185 undergraduates, Grizzard and colleages (2014) studied the relationship between virtual-world immoral behavior and its real-world effects. Participants were place in either a guilt-inducing condition (playing the game as a terrorist) or a control condition (playing the game as a UN soldier). Results indicated that not only did participants in the terrorist-condition experience greater guilt after the fact, but also experienced intuition-specific increases in the salience of violated moral values. These findings suggest that behaviors we commit in the virtual world can elicit responses in us the same way that real-world behavior does. The literature, however, is not all negative: similar causal effects have been found between relaxing video games and increased prosocial behavior, as well as decreased anti-social behavior (Whitaker & Bushman, 2012). With such evidence of the reciprocal influence of our real- and virtual- world behaviors, there is strong support for continued examination of our virtual social behavior.

Demographics of the typical gamer. Every year, the Entertainment Software Association (ESA) contracts a third party entity to conduct a non-refereed study of video game users. In its latest publication, the ESA (2014) surveyed more than 2,200 nationally representative American households, and found that 58% of Americans play video games, and 51% of households have a dedicated gaming device. Separately, Lenhart and colleagues (2008) found that, in a nationally representative sample of 1,102 12- to 17-year-olds, 97% of teens play video games; nearly one-third (31%) of these teen gamers play every day, and another 21% play video games three to five days a week. This substantial adolescent participation likely contributes to the common belief that video games are primarily limited to teenage males. Contrary to this popular notion, the average age of a gamer is 31-years-old, with an approximately equal distribution among the age groups of < 18 years, 18-35 years, and > 35 years (ESA, 2014). Thus, 68% of gamers are 18 or older. Furthermore, the ESA (2014) found that males make up only 55% of gamers. However, this distribution is not even across all types games played (Lenhart et al., 2008).

Measuring social behavior. By introducing the notion of using measurement of video-game behavior to infer actual social behavior, we must address the question, "How else have we tried to measure pro-social and anti-social behavior?" This has been done in several ways.

Previous methods. Quantifiable measures of pro-social and anti-social behavior are nothing new to psychology. In fact, there are a variety of different methods for doing so, and each method presents its own advantages and drawbacks.

Self-report questionnaire. A common method of measuring social behavior is the self-report questionnaire, in which participants are asked about their social behaviors and respond with the frequency of or tendency towards those behaviors (e.g., Kavussanu & Boardley, 2009). These questionnaires may assess either state or trait pro-sociality and anti-sociality measures. This is arguably the most efficient method of measurement, given its straightforwardness and lack of cost. It is the method from which the Sociality in Multiplayer Online Games Scale (SMOG), developed for this present study, is modeled (see Method: Measures below.)

Self-report questionnaires provide the most time- and cost-efficient method of measurement. Questionnaires can be conducted online, eliminating the need to bring in participants. Furthermore, questionnaires can maintain anonymity, which increases self-disclosure and lowers social desirability. Yet even through computers, self-report questionnaires are always subject to the social desirability bias, in which participants may not answer truthfully to appear more pro-social than they actually are. Additionally, self-report questionnaires only provide a singular (and inherently biased) perspective.

Third-party ratings. Another common method of measuring social behavior is the third-party rating questionnaire, in which participants are asked about *another individual's* social behaviors, and they respond with their perception of the frequency of or tendency towards those behaviors (e.g., Bracken, Keith, & Walker, 1998). Third-party ratings may also encompass state or trait measures. This is another simple and efficient method of measuring social behavior. Similar to the self-report questionnaire, it is straightforward and incurs limited cost for the researchers. However, it does introduce the added level of another person's perception of a participant's behavior—with its own attendant problems.

Similar to the self-report questionnaire, the third-party ratings are both time and cost efficient; questionnaires are simple, anonymous, and may be completed without the need of a laboratory. These also remove some of the bias of self-report. Yet third-party participants may not be able to accurately report the social behavior of the target individual due to lack of knowledge. Or, rather than accidental inaccurate results, third-party participants may intentionally cast the individuals in a certain light, depending on their affiliation with the target individual.

Scenario-response coding. In scenario-response ratings, participants are provided with a scenario in which they may respond either pro-socially or anti-socially. The central idea is that participants are not directly asked about their behaviors; instead, their behaviors are directly observed by the researchers. Additionally, the scenario provides restrictions to the possible participant responses, allowing for easier coding. These responses can be textual (as in Linguistic coding; Masten, Morelli, & Eisenberger, 2011), non-verbal (e.g., the Facial Action Coding system; Ekman & Friesen, 1977), or specific, quantifiable behaviors, such as pouring hot sauce for another person to drink (e.g., Lieberman, Solomon, Greenberg, & McGregor, 1999). These behaviors are observed by the researchers and then coded accordingly.

One of largest advantages of scenario-response coding is that participants are not directly asked about their behaviors, eliminating some of the bias associated with social desirability. Yet it is important to note that, when being observed, social desirability is always of concern. Additionally, scenario responses provide a more controlled environment than real-world coding, allowing for greater specification of behaviors. Finally, while not as efficient as questionnaires, scenario response coding provides more time- and cost- efficiency than real-world coding; however, the commensurability of hot sauce to negative feelings towards a person is questionable. And, given the nature of the scenario and the responses, scenario response coding can have varied real-world application.

Real-world coding. Another method of measuring social behavior, and usually the most time-consuming, is real-world coding. This method involves coding behaviors derived from transcripts or videos of real-world, uncontrolled interactions into their appropriate pro-social or anti-social categories.

The greatest advantage of real-world coding is its external validity and real-world application. By observing participants in genuine social interactions, researchers do not need to worry about the atypical environment of a laboratory nor the influence of the presence of researchers. On the other hand, one must be concerned about the validity of such a small sample of one’s behavior at reflecting a dispositional trait. Yet with its enormous advantages come equally impactful disadvantages: real-world coding is massively time- and cost-consuming, making it a less-preferred choice in behavioral science research.

Diary coding. The final method of measuring pro-social and anti-social behavior, a more recently developed method, is diary coding, in which behavior is recorded out of participants' daily lives. Participants carry with them a device (typically a smart phone) that contains an application. Participants can use the application to answer questions about their social interactions, without having to access a laboratory or computer. Responses may be elicited using *experience sampling* (asking after every social interaction), *event sampling* (asking after a particular event), or *time sampling* (asking at a consistent time of day; e.g., Bolger, Davis, & Rafaeli, 2003)

Diary coding has provided a fast, direct method of measuring pro-social and anti-social interactions from participants. Responses can be elicited in-moment, and therefore are not subject to the faultiness of respondent memory. Additionally, participants might feel comfortable using their smart phones, given their familiarity with the device. Unfortunately, diary coding requires more resources and expertise than do more traditional methods of measurement—developing the application, programming the devices, and providing devices to participants who do not already have them all contribute to a costly study.

Desirability of multiple measures. In practice, it is ideal to use multiple methods of measuring behavior. Combinations of the above methods can allow us to triangulate measurements, creating a more valid score. With attentions shifting towards social interaction in online gaming, there is a need for validated measures based in online social gaming behavior.

Discussion of the review.

Overall status of the field. Social interaction in the context of virtual worlds has been examined thoroughly, and three general themes have arisen. First, people generally behave similarly online as they do in the real world (e.g., Graham & Gosling, 2012). Second, people are more likely to act immorally, or behave in more socially unacceptable ways, when interacting online (e.g., Bandura, 1999; Joinson, 2001). Third, there is a reciprocal influential relationship between our virtual- and real-world behaviors (e.g., Whitaker & Bushman, 2014).

Needed studies in the field. Formal measures of social behavior in online games are currently non-existent. While *ad hoc* measures have been utilized (e.g., the emission of positive emotes in World of Warcraft; Yee, Ducheneaut, & Nelson, 2011), these have been game-specific and therefore not applicable for broader use. Additionally, a disproportionate amount of research has focused on the effect of violence in video games on behavior (e.g., Griffiths, 1999; Anderson et al., 2010), as opposed to various other gaming factors that might influence our behavior. The capacity for social interaction and influence in online gaming has grown, and there is greater opportunity and need to empirically examine it in more and larger contexts.

Purpose of the current studies. The purpose of the current study is two-fold: first, to create a scale measuring the frequency of certain behaviors in the context of the team-based, multiplayer online games; and second, to examine the construct validity of interpersonal orientation – characterized by dominance and affiliation (Kiesler, 1982) – on these behaviors.

In the current studies, I created a scale to measure online gaming behaviors, consisting initially of 77 items. I collected two separate samples. The first, reported in Study 1 (N=250), I used for winnowing of items and refinement of the scale. The second sample, reported in Study 2 (N=104), I used to test psychometric properties of the scale using confirmatory factor analysis, and to provide for initial construct validity data.

Study 1

In Study 1, I created a scale to measure online gaming behaviors. I then sought to use exploratory factor analyses to determine a simple structure.

Method

Participants. Participants for Study 1 included a worldwide sample of *N=266* adult volunteers recruited from internet postings and campus out-reach. Of the participants, *n* = 16 participated in the focus groups. In the online survey, *n* = 250 participated.

Demographics. Of the participants, *n*= 193 (77%) identified as male; *n*=50 (20%) identified as female, and the remaining *n*= 5 (3%) identified as transgender or other. Participant ages ranged from 18 to 50 (Mean = 21.22, *Md* = 20, *Mo* = 18). Of the participants, *n*= 156 (62.4%) identified as Non-Hispanic White or Euro-American, *n*=29 (11.6%) identified as East Asian or Asian American, *n*=11 (4.4%) identified as Latino/Latina or Hispanic-American, and the remaining (21.6%) identified as a variety of other ethnicities. Through a worldwide sample, *n*=159 (63.6%) of participants reported living in North America; *n*=70 (28%) reported living in Europe. Of the participants, *n*=168 (67.7%) reported currently being in school.

Inclusion and exclusion criteria. Of the 402 participants who consented to participate in the study, 115 responses were eliminated due to incomplete responses; an additional 31 responses were eliminated due to failure to accurately respond to validation questions. In order to be considered for this study, participants must have been 18 or older at the time of survey completion. Additionally, participants for Study1 were limited to a population of gamers who played the online game League of Legends (developed by Riot Games) for at least one month.

Justification for League of Legends. In its development, the SMOG was intended to measure pro-social and anti-social behavior in the context of a particular game, League of Legends ("League"). I chose this game for several reasons. First, it is the most played and most spectated online game in the world (Gaudiosi, 2012). According to a 2013 infographic released by *Twurdy.com,* there are 70 million registered users, and 32.5 million daily active players (Pereira, 2013). That's equal to approximately 10% of the US population playing every day. Per month, League boasts approximately 1.3 billion hours of gameplay (Pereira, 2013). That's equal to over 148,000 years' worth of time played every month. Second, League has permeated through several cultures – specifically in East Asia – allowing for future cross cultural research (Gaudiosi, 2012). Third, League requires consistent communication and interaction between players and is notorious for its frequently hostile and "toxic" environment. And fourth, League was at the forefront of the recent adoption of eSports as an official sport in the United States (Gafford, 2013). Fifth, it provides a team-based and competitive environment that allows a range of social behaviors. Thus it provides the opportunity for players to act in ways that might approximate their behavior in other social situations (especially those involving teamwork and competition).

Measures.

Sociality in Multiplayer Online Games-77 (SMOG-77). To measure the frequency of online gaming behaviors in League, the SMOG-77 was developed. Through collaboration with two focus groups (n = 8, n = 8), two content experts and two scale development experts, 77 items were compiled. Each item is a statement about gaming behaviors; the participants can respond on an 8-point rating, ranging from 0 = *never,* to 7 = *always.* A sample item for the scale is, "I consult my teammates during Champion Select before I select/lock in my own preference." Along with these behavioral frequency items, participants are also asked about their history playing the game (e.g., How many hours per week do you play? What is your ranking, if you play ranked?)

The scale was devised by seeking to generate items related to 12 conceptual dimensions, each pertaining to a specific behavior in the game. Each conceptual dimension contributed to approximately 5-7 of the items. Conceptual dimensions included Instalocking, Trolling, Role Choice, Leadership style, Autonomy/cooperation, Teaching, Resource stealing, Resource forfeiting, Raging, Enemy support, Building positive rapport, and Post-Game reports. (For definitions of these terms, please see Appendix A). I hypothesize that, (a) questions within each conceptual dimension will elicit similar responses, and (b) responses to each conceptual dimension will correlate to responses on the measure of dominance and affiliation. (Please see Appendix B for SMOG-77.)

Procedure.

Recruitment. Participants Study 1 were recruited through two major media. Undergraduate students from Virginia Commonwealth University were recruited through SONA Systems. Participants were also recruited through campus and social media outreach, including university clubs (e.g., LOL@VCU), online forums (e.g., Reddit), and online social media (e.g., Facebook groups).

Data collection. Study data were collected and managed using REDCap electronic data capture tools hosted at Virginia Commonwealth University. REDCap (Research Electronic Data Capture) is a secure, web-based application designed to support data capture for research studies. Data were collected at a single time point and analyzed after collection was complete.

Results

Data cleaning. Data were cleaned and study measures were created using IBM Statistics SPSS – Version 22 (IBM Corp., 2013). The data were checked for lack of normality, linearity, and homoscedasticity of the residuals through examination of basic statistics and histograms.

Because less than 2% of the item-level data were missing, findings may be considered free of bias that is typically attributed to incomplete data (Tabachnick & Fidell, 2001).

Focus groups and item generation. Through these focus groups, a list of different social behaviors observed over the course of the game was created. Both groups consisted of 8 participants and were led by researcher Chelsea Hughes. Chelsea was non-active in item generation; she served to prompt the group to discuss social behaviors. As a group, infrequent concepts were eliminated (those that were not agreed upon by any other group member), and redundant concepts (two or more behaviors that measured the same concept; e.g., Autonomy/Cooperation) were combined. From categorization of responses from these focus groups, I identified 12 conceptual dimensions. They were examined in the questionnaire. Once the 77 items were created, content experts (two employees of Riot Games) and scale development experts (two Ph.D.s in Psychology who had experience publishing articles reporting development of scales and psychometrics) were consulted. Five of the 77 items were revised for clarity, resulting in the SMOG-77 (see Appendix B). These dimensions, or behaviors, are listed and defined in Appendix A.

Prior to analyzing the data, I removed 25 items due to game specificity. Because the ultimate goal was to create a measure applicable to all team-based multiplayer online games, the items pertaining to behaviors Instakill, Resource stealing, Resource forfeiting, and Post-Game Reports were removed. This resulted in the 52 items retained for the factor analysis, or the SMOG-52.

Exploratory Factor Analysis (EFA) on SMOG-52. An EFA with Principal Axis Factoring and Direct Oblimin rotation was conducted on the SMOG-52. The scree plot suggested 3-4 factors; therefore, the EFA was rerun using Principal Axis Factoring and a Direct Oblimin rotation, requesting specifically 4 factors. For items to be retained, they must have loaded at least .60 on the primary factor, and no greater than .30 on any other factor. The factor loadings revealed that items on Factor 4 only consisted of reverse-coded items; therefore, 3 factors were considered more likely. Additionally, none of the 4 factors correlated with another exceeding $r = |.19|$; I therefore determined that the factors were orthogonal.

An EFA using Principal Axis Factoring and a Varimax Rotation was conducted on the SMOG-52; 3 factors were requested. Items were retained using the same primary- and cross-loading criteria. I eliminated 34 items, reducing the measure from 52 to 18 items. An EFA using Principal Axis Factoring and Varimax Rotation, requesting 3 factors, was run on the remaining 18 items. Two additional items were eliminated due to insufficient primary loading (< .60). An EFA (Principal Axis Factoring, Varimax Rotation, 3 factors requested) was run on the remaining 16 items (i.e., SMOG-16). These factor loadings are presented in Table 1.

Table 1.

Factor loadings of SMOG-16

	Factor		
Item	1	2	3
trolling1	**.860**	-.030	-.081
trolling2	**.836**	-.038	-.044
trolling3	**.782**	-.047	-.016
trolling5	**.783**	-.079	-.051
role1	.065	.119	**.910**
role5	.029	.067	**.676**
role4r	-.015	-.019	**.728**
rage2	**.666**	.067	.134
rage5	**.661**	-.009	.179
teach1	.050	**.721**	.069
teach2	.158	**.763**	.145
teach3	.050	**.810**	.094
teach5	.129	**.623**	.078
rapp1	-.223	**.717**	-.067
rapp2	-.197	**.649**	.016
rapp4	-.143	**.661**	-.074

Upon examining the items of the 3 factors, it became clear that Factor 3 contained only 3 highly redundant items from a single behavior; furthermore, these items could be attributed to the types of characters played in the game, as opposed to social interaction in the game (e.g., "I play carry-type roles" and "I play with high damage output.") Therefore, based on the redundancy of items and the goal of measuring social interaction, 2 factors were considered more suitable.

An EFA (Principal Axis Factoring, Varimax Rotation, 2 factors requested) was run on the SMOG-16. The three items from the third factor were eliminated due to insufficient primary factor loading. The EFA was rerun using only the remaining 13 items; these items met all criteria and constitute the SMOG-13. (See Table 2 below for factor loadings.)

Table 2.

Factor loadings of SMOG-13

	Factor	
Item	1	2
trolling1	**.85**	-.037
trolling2	**.831**	-.042
trolling3	**.781**	-.052
trolling5	**.775**	-.087
rage2	**.670**	.078
rage5	**.664**	.007
teach1	.053	**.728**
teach2	.163	**.773**
teach3	.053	**.817**
teach5	.132	**.629**
rapp1	-.227	**.705**
rapp2	-.199	**.644**
rapp4	-.147	**.650**

In order to reduce the redundancy of the scale, I examined the inter-correlations of the items within each factor. The inter-item correlations of the two factors of the SMOG-13 can be found in Tables 3 and 4.

Upon examining these tables, I further eliminated two redundant items. This resulted in the final measure of Study 1, the SMOG-11 (see Appendix C). The items, factor loadings, item means, standard deviations, and communalities for the SMOG-11 are presented in Table 5.

Table 3.

Inter-item correlations of SMOG-13 Factor 1

	1	2	3	4	5
1. trolling1	--				
2. trolling2	.801**	--			
3. trolling3	.681**	.550**	--		
4. trolling5	.673**	.673**	.597**	--	
5. rage2	.433**	.476**	.528**	.401**	--
6. rage5	.453**	.533**	.482**	.458**	.674**

** $p < .001$

Table 4.

Inter-item correlations of SMOG-13 Factor 2

	1	2	3	4	5	6
1. teach1	--					
2. teach2	.713**	--				
3. teach3	.647**	.751**	--			
4. teach5	.481**	.532**	.609**	--		
5. rapp1	.418**	.398**	.479**	.351**	--	
6. rapp2	.377**	.349**	.442**	.339**	.697**	--
7. rapp4	.380**	.390**	.434**	.344**	.708**	.585**

** $p < .001$

Upon examining the items of each factor, I determined that Factor 1 consisted of anti-social, or destructive social behaviors. This included raging, defined as expressing excessive verbal aggression towards other players (2 items), and trolling, defined as intentionally making the game unpleasant for one's teammates (4 items). Factor 2, on the other hand, consisted of items that endorsed pro-social, or constructive social behaviors. This included teaching other players how to play the game and rapport-building behaviors. Therefore, these factors were entitled the SMOG-Destructive (α = .85) and SMOG-Constructive (α = .85).

Table 5.

*Items, Factor Loadings, Item Means, Standard Deviations, and Communalities for the SMOG-11 (*N=*250)*

Item	Factor Loadings 1	Factor Loadings 2	*M*	*SD*	h^2
1. I intentionally make the game unpleasant for my teammates.	**.765**	-.045	.436	.815	.587
2. I have intentionally performed poorly in a game.	**.716**	-.055	.588	1.019	.515
3. I enjoy making the game suck for my teammates.	**.725**	-.112	.324	.719	.538
4. I get verbally aggressive with other players.	**.706**	.066	1.260	1.426	.502
5. I have been described as a toxic player.	**.736**	-.009	.791	1.288	.541
6. If I am more skilled or knowledgeable than my teammates, I share my knowledge with them.	.060	**.658**	4.394	1.698	.437
7. If I am a stronger player than m y peers, I try to help the weaker players improve their gameplay.	.085	**.754**	4.061	1.610	.576
8. I take up the responsibility to help other players improve.	.147	**.609**	3.298	1.566	.392
9. I encourage my teammates during gameplay.	-.225	**.772**	4.446	1.591	.646
10. If my teammates make a good play, I congratulate them.	-.185	**.701**	5.256	1.447	.526
11. I try to build a sense of team unity in chat.	-.147	**.701**	3.807	1.816	.513

Discussion of Study 1

In Study 1, I found evidence for a two-factor model explaining social behavior in online games. Based on the item content of these two subscales, they appear to represent anti-social and pro-social behavior, which I have labeled "Destructive" and "Constructive."

These findings reflect the work of Kavussanu and colleagues (2006, 2009), who have observed similar, anti-social and pro-social dichotomies in their work with social behavior in traditional athletes. Also similar to Kavussanu's work, I found negligible correlations – either small or nonsignificant – between the two factors. This might suggest that enacting pro-social behavior in sports does not disqualify an athlete from also enacting anti-social behavior.

Study 2

In Study 2, I conducted a Confirmatory Factor Analysis to provide further evidence of a two-factor structure of the SMOG-11. I hypothesized that a similar pro-social and anti-social factor structure would replicate in a separate sample. I also conducted a hierarchical multiple regression, using measures of dominance and affiliation, to assess construct validity of the SMOG. I hypothesized that both SMOG-Destructive and SMOG-Constructive scores would predict dominance. I also hypothesized that SMOG-Destructive would negatively predict affiliation, whereas SMOG-Constructive would positively predict affiliation.

Method

Participants. Participants for Study 2 included N=104 adult volunteers.

Demographics. Of the participants, n= 46 (44%) identified as male; n=55 (53%) identified as female, and the remaining n= 1 (1%) identified as transgender or other. Participant ages ranged from 18 to 41 (Mean = 20.97, Md = 20, Mo = 18). Of the participants, n= 50

(48.1%) identified as Non-Hispanic White or Euro-American, *n*=16 (15.4%) identified as Black or African American, *n*=11 (10.6%) identified as East Asian or Asian American, *n*=9 (8.7%) identified as Latino/Latina or Hispanic American, and the remaining (10.6%) identified as a variety of other ethnicities. Through a worldwide sample, *n*=98 (94.2%) of participants reported living in North America. Of the participants, *n*=94 (96.2%) reported currently being in school.

Inclusion and exclusion criteria. Of the 126 participants who consented to participate in the study, 22 responses were eliminated due to incomplete responses. To be considered for this study, participants must have played any team-based, multiplayer online game for at least one month.

Measures.

Sociality in Multiplayer Online Games (SMOG-11). The SMOG-11 consists of the 11 items that were retained from the Exploratory Factor Analysis conducted on the SMOG-77 (see Study 1). The scale consists of two orthogonal factors, or subscales: the SMOG-Constructive (7 items), which measures the frequency of constructive (or pro-social) behavior, and the SMOG-Destructive (6 items), which measures the frequency of destructive (or anti-social) behavior. (Please see Appendix C for SMOG-11).

Affiliation and dominance: The Interpersonal Adjective Scale Revised Big-Five (IASR-B5). The Interpersonal Adjective Scale Revised Big-Five (IASR-B5; Trapnell & Wiggins, 1990) is a 124-item scale that measures the Big 5 personality traits (Neuroticism, Extroversion/Surgency, Openness to experience, Conscientiousness, and Agreeableness), including markers of the interpersonal circumplex coordinates of dominance and nurturance (comparable to Kiesler's (1982) interpersonal circle). In the case of this present study, I am using only the Affiliation (Conscientiousness) and Dominance (Extraversion/Surgency) subscales, totaling 32 items. The IASR-B5 provided alphas ranging from .87 to .94 (Trapnell & Wiggins, 1990), and acceptable convergent properties when compared to the NEO-Personality Inventory (a fellow measure of the Big 5 personality traits), with high correlations ranging from .67 to .76 (Openness and Agreeableness, respectively). Participants are asked to rate the degree to which they believe an adjective describes themselves (e.g., dominant). Responses are recorded on an 8-point rating ranging from 0=*extremely inaccurate* to 7=*extremely accurate*. Alpha coefficients range from .77 to .88.

Procedure.

Recruitment. Participants for Study 2 were recruited through two major media. Undergraduate students from Virginia Commonwealth University were recruited through SONA Systems. Participants were also recruited through campus and social media outreach, including university clubs (e.g., LOL@VCU), online forums (e.g., Reddit), and online social media (e.g., Facebook groups).

Data collection. Study data were collected and managed using REDCap electronic data capture tools hosted at Virginia Commonwealth University. REDCap (Research Electronic Data Capture) is a secure, web-based application designed to support data capture for research studies. Data were collected at a single time point and analyzed after collection was complete.

Results

Confirmatory Factor Analysis (CFA).

SMOG-11. To assess whether the 2-factor structure observed in the EFA would replicate in a separate sample, a confirmatory factor analysis (CFA) was conducted on the SMOG-11. The overall fit for the two-factor model of the SMOG-11 was poor, $\chi^2(43) = 162.322$, $p < .001$; $\chi^2/df = 3.775$; CFI = .801; RMSEA = .163, 95% CI [.137-.190].

Due to the strong theoretical rationale for a two-factor structure (pro-social and anti-social behavior), as well as the convincing results of the EFA, I sought to winnow the 11-item measure to better fit the model. I therefore eliminated two redundant items from the SMOG-Destructive, and three items from the SMOG-Constructive, due to conditional phrasing. This resulted in six remaining items, three per factor (see SMOG-6 in Appendix D).

SMOG-6. A CFA was conducted on the Study 2 (N = 104) participants to assess the fit of the SMOG-6 in an independent sample with the 2-factor model observed in Study 1. The overall fit with the model was excellent, $\chi^2(8) = 9.759$, $p = .282$; $\chi^2/df = 2.088$; $CFI = .99$; $RMSEA$ = .046, 95% CI [.000 - .129]. The primary factor loadings ranged between .37-.76 for the SMOG-Destructive, and between .71-.89 for the SMOG-Constructive (see Table 6). Alphas (α) for SMOG-Destructive and SMOG-Constructive were .57 and .86, respectively.

Two additional CFAs were conducted using the sample from Study 1 (N = 250) and a reconstituted full sample (N = 354) to compare the fit statistics across multiple samples. These results largely reflected those found in the Study 2 sample. The fit statistics of both samples are presented, χ^2/df = 1.22, 2.08; CFI = .978, .984; $RMSEA$ = .056, .067; $SRMR$ = .046,.049, for the Study 2 sample and the combined samples, respectively. Alphas for SMOG-Destructive and SMOG-Constructive ranged between .70-.75, and .72-.79, respectively. For subscale alphas and CFA primary factor loadings, and additional fit statistics of the SMOG-6 across the three samples, see Tables 6 and 7.

Evidence Related to the Construct Validity of the SMOG-6. To measure the predictive validity of the SMOG-6 on pro-social and anti-social behavior, two multiple linear regressions were conducted on each of the three samples. Responses on each factor were added for cumulative SMOG-Destructive and SMOG-Constructive scores. I hypothesized that, when controlling for age, gender, and frequency of gameplay, both SMOG-Destructive and SMOG-Constructive would positively predict dominance (H1 and H2); SMOG-Destructive would negatively predict affiliation (H3); and SMOG-Constructive would positively predict affiliation (H4).

Table 6.

Alphas and CFA Primary Factor Loadings of the SMOG-6

Item	Sample 1 N = 250		Sample 2 N = 104		Reconstituted Sample N = 354	
	D	C	D	C	D	C
2. I have intentionally performed poorly in a game.	**.909****	--	**.560****	--	**.795****	--
3. I enjoy making the game suck for my teammates.	**.694****	--	**.763****	--	**.692****	--
4. I get verbally aggressive with other players.	**.621****	--	**.372***	--	**.531****	--
8. I take up the responsibility to help other players improve.	--	**.400****	--	**.705****	--	**.486****
9. I encourage my teammates during gameplay.	--	**.886****	--	**.883****	--	**.883****
11. I try to build a sense of team unity	--	**.764****	--	**.863****	--	**.809****
Cronbach's α =	.75	.72	.57	.86	.70	.79

Note. D=Destructive; C=Constructive
*- $p < .05$
**-$p < .001$

Table 7.

Fit Statistics for the SMOG-6 across Three Samples

Sample	$\chi^2(df)$	*p*	χ^2/df	*CFI*	*RMSEA*	*95% CI*	*SRMR*
N = 250	16.702(8)	.282	1.22	.979	.067	.018-.112	.048
N = 104	9.759(8)	.033	2.088	.990	.046	.000-.129	.046
N = 354	16.607(8)	.034	2.076	.984	.056	.014-.094	.046

SMOG-Destructive and SMOG-Constructive will predict dominance (H1 and H2). In all three samples, the overall model was a significant predictor of dominant personality, $F(6, 319) = 8.159$, $p < .001$, R^2=.135. (Note: the findings reported represent the reconstituted full sample; the independent results from Study Sample 1 and Study Sample 2 are presented in Table 8). Together, the SMOG-Destructive and SMOG-Constructive predicted 13.5% of the variance in dominant personality. Consistent with our hypotheses, SMOG-Destructive score, $t(319)$ = 3.32, p = .001, β = .176, and SMOG-Constructive score, $t(319)$ = 3.87, $p < .001$, β = .205, were both individual positive predictors of dominant personality (see Table 8).

SMOG-Destructive will negatively predict affiliation; SMOG-Constructive will positively predict affiliation (H3 and H4). In all three samples, the overall model was a significant predictor of affiliative personality, $F(6, 313) = 11.963$, $p < .001$, R^2=.189. (Note: the findings reported represent the reconstituted full sample; the independent results from the Study Sample 1 and Study Sample 2 are presented in Table 8). Together, the SMOG-Destructive and SMOG-Constructive predicted 18.9% of the variance in affiliative personality. Consistent with our hypotheses, SMOG-Destructive was a significant negative predictor of affiliation, $t(313)$ = -

3.97, $p < .001$, $\beta = -.206$; whereas SMOG-Constructive score was a significant positive predictor of affiliation, $t(313) = 4.03$, $p < .001$, $\beta = .209$ (see Table 8).

Table 8.

Predictive Value of the SMOG-D and SMOG-C on Affiliation and Dominance

Criterion Variable: Dominance

	F	$df1, df2$	R^2	β	t	df
Sample 1 ($N = 250$)	5.373**	6, 223	.129	--	--	--
SMOG-D	--	--	--	.138	2.135*	223
SMOG-C	--	--	--	.180	2.793*	223
Sample 2 ($N = 104$)	4.063*	2, 95	.215			
SMOG-D	--	--	--	.198	2.087*	95
SMOG-C	--	--	--	.259	2.604*	95
Reconst. Sample ($N = 354$)	8.159**	6, 319	.135	--	--	--
SMOG-D	--	--	--	.176	3.32*	319
SMOG-C	--	--	--	.205	3.87**	319

Criterion Variable: Affiliation

	F	$df1, df2$	R^2	β	t	df
Sample 1 ($N = 250$)	5.358**	2, 216	.133	--	--	--
SMOG-D	--	--	--	-.184	-2.802*	216
SMOG-C	--	--	--	.195	2.988*	216
Sample 2 ($N = 104$)	9.047**	6, 96	.376	--	--	--
SMOG-D	--	--	--	-.261	-3.111*	96
SMOG-C	--	--	--	.237	2.687*	96
Reconst. Sample ($N = 354$)	11.963**	6, 313	.189	--	--	--
SMOG-D	--	--	--	-.206	-3.97**	313
SMOG-C	--	--	--	.209	4.03**	313

* $p < .05$
** $p < .001$
Note. This analysis controlled for age and gender (box 1) and frequency and duration of gameplay (box 2)

Discussion of Study 2

In the present study, I have provided further evidence of the two-factor structure found in Study 1. Furthermore, I found that high dominance is associated with destructive (anti-social) and constructive (pro-social) behaviors. I also found that affiliation is associated with these behaviors: constructive behaviors positively predict affiliation, and destructive behaviors negatively predict affiliation. In Appendix E, Table E-1, I have provided a table of norms for the combined samples—both recruited from the internet.

The predictive value of the SMOG-Destructive and SMOG-Constructive on affiliative personality supports current literature on the Big-Five personality trait of agreeableness. According to Graziano and Tobin (2009), individuals high in agreeableness – also known as affiliation- tend to show higher degrees of motivation to enact positive, constructive social behaviors. The results of Study 2 reflect this notion, where SMOG-Constructive positively predicts agreeableness, and SMOG-Destructive negatively predicts it.

The predictive value of dominance and affiliation on the SMOG-6 present an interesting parallel with bullying literature. Research has consistently shown that bullies and those who intervene to interrupt bullying tend to score higher in dominance than victims and non-active observers (e.g., Olthof et al., 2011; Tani, Greenman, Schneider, & Fregoso, 2003). It is the dominant individuals who are actively doing good or doing bad in the community. I see a similar relationship in the constructive and destructive behaviors in the online game: the dominant individuals are verbally aggressing and making the game more difficult for teammates – but also congratulating teammates and helping them improve their gameplay. Research has also shown that affiliation negatively predicts bullying and positively predicts anti-bullying, or bully-intervention (Tani, Greenman, Schneider, & Fregoso, 2003). Reflectively, affiliation negatively predicts destructive social gaming behaviors and positively predicts constructive social gaming behaviors. The personality trait of affiliation can not only predict who can do harm and do good in the real world, but also in the virtual world.

General Discussion

In Study 1, I found that responses to the gamming questionnaire were best described by a two-factor structure, seemingly modeled after anti-social behavior and pro-social behavior. In Study 2, Confirmatory factor analysis supported this two factor structure, resulting in the creation of the SMOG-6. Each of the factors predicted interpersonal orientation, characterized by dominance and affiliation.

These findings support the literature that suggests that real-world personality can predict virtual-world behavior. (Graham & Gosling, 2012; Greitemeyer & Cox, 2013; Ma, Li, & Pow, 2011; Yee, Ducheneaut, Nelson, & Likarish, 2011) An abundance of research has shown that individuals high in trait dominance tend to enact more influence in face-to-face group settings (for a review, see Judge, Bono, Ilies, & Gerhardt, 2002). We see this paralleled in the virtual world, where dominant individuals are the ones who are deliberately enacting constructive and deconstructive interpersonal behaviors. Research has also shown that individuals high in affiliation tend to favor interpersonal harmony and cooperation in face-to-face interactions. (Anderson, John, Keltner, & Kring, 2001; Graziano & Tobin, 2009) According to our findings, this tendency is reflected in the virtual world, as well.

Limitations

There are several limitations to the study. The SMOG-6 is memory-based and self-reported, which increased our measurement error. The SMOG-Destructive and SMOG-Constructive need to be compared to actual gaming behavior to establish strong evidence for criterion-related validity. Finally, further measures assessing pro-social and anti-social behavior should be compared to the SMOG-6, to establish construct validity of the SMOG-Destructive and SMOG-Constructive.

Directions for Future Research

Given the limitations of this study, future research should strive for measures of the behavior indices that test the SMOG-6 against actual gaming behaviors – namely, to record and code these behaviors as they occur in game. Additionally, both self-report and third-party ratings should be used to measure affiliation and dominance, given the biases associated with only self-report data. It will also be necessary to assess social behavior beyond Kiesler's (1983) theory of interpersonal orientation by examining the relationship between these behaviors and various other personality theories (e.g., Big Five).

Implications for Practice and for General Use of Gaming

The results of the present study also open the doors for practical application of personality's effect on in-game social behavior. With such an influence of personality on in-game behavior, it is possible that real-world personality interventions may also alter social behavior in online gaming. Conversely, perhaps interventions implemented by game developers might result in changes in real-world personality. This would create an entirely new medium for implementing covert interventions, gaining access to a massive population and reducing the stigma surrounding psychological interventions in both clinical and non-clinical populations. Additionally, unlike previous research in online gaming, the behaviors examined in this study have notable impact on a player's (and team's) success in the game (e.g., verbal aggression resulting in decreased performance). With the recognition of eSports as an official sport, this line of research may find use in the field of sports psychology and performance enhancement.

List of References

List of References

Anderson, C., John, O. P., Keltner, D., & Kring, A. M. (2001). Who attains social status? Effects of personality and physical attractiveness in social groups. *Journal of Personality and Social Psychology, 81*(1), 116.

Anderson, C. A., Shibuya, A., Ihori, N., Swing, E. L., Bushman, B. J., Sakamoto, A., ... & Saleem, M. (2010). Violent video game effects on aggression, empathy, and prosocial behavior in eastern and western countries: a meta-analytic review. *Psychological bulletin, 136*(2), 151.

Bandura, A. (1999). Moral disengagement in the perpetration of inhumanities. *Personality and Social Psychology Review*, *3*(3), 193-209.

Bateson, M., Nettle, D., & Roberts, G. (2006). Cues of being watched enhance cooperation in a real-world setting. *Biology Letters*, *2*(3), 412-414.

Berger, J., Cohen, B. P., & Zelditch Jr, M. (1972). Status characteristics and social interaction. *American Sociological Review*, *37,* 241-255.

Bolger, N., Davis, A., & Rafaeli, E. (2003). Diary methods: Capturing life as it is lived. *Annual Review of Psychology*, *54*(1), 579-616.

Bowman, N. D., Weber, R., Tamborini, R., & Sherry, J. (2013). Facilitating game play: How others affect performance at and enjoyment of video games. *Media Psychology*, *16*(1), 39-64.

Caplan, S. (2003).Preference for online social interaction: A theory of problematic Internet use and psychosocial well-being. *Communication Research, 30*, 625–648.

Caplan, S., Williams, D., &Yee, N. (2010).Problematic Internet use and psychosocial well-being among MMO players. *Computers in Human Behavior, 25*(6), 1312–1319.

Davis, R. ,Flett, G.,& Besser, A.(2002).Validation of a new scale for measuring problematic internet use: Implications for pre-employment screening. *Cyberpsychology and Behavior, 5*(4), 331–345.

Entertainment Software Association. (2014). *2014 essential facts about the computer and video game industry.* Retrieved from <http://www.theesa.com/facts/pdfs/ESA_EF_2014.pdf>.

Gaudiosi, John. (11 July 2012).Riot Games' League Of Legends officially becomes most played PC game in the world. *Forbes*. Retrieved from http://www.forbes.com/sites/johngaudiosi/2012/07/11/riot-games-league-of-legends-officially-becomes-most-played-pc-game-in-the-world/

Gosling, S. D., Augustine, A. A., Vazire, S., Holtzman, N., & Gaddis, S. (2011). Manifestations of personality in online social networks: Self-reported Facebook-related behaviors and observable profile information. *Cyberpsychology, Behavior, and Social Networking*, *14*(9), 483-488.

Graham, L. T., & Gosling, S. D. (2012). Impressions of World of Warcraft players' personalities based on their usernames: Interobserver consensus but no accuracy. *Journal of Research in Personality*, *46*(5), 599-603.

Granic, I., Lobel, A., Engels, R. C. M. E. (2014). The benefits of playing video games. *American Psychologist, 69*(1), 66-78.

Graziano, W. G., & Tobin, R. M. (2009). Agreeableness. *Handbook of individual differences in social behavior.* New York, NY: Guildford Press.

Greitemeyer, T., & Cox, C. (2013). There's no "I" in team: Effects of cooperative video games on cooperative behavior. *European Journal of Social Psychology*, *43*(3), 224-228.

Griffiths, M. (1999). Violent video games and aggression: A review of the literature. *Aggression and violent behavior, 4*(2), 203-212.

Grizzard, M., Tamborini, R., Lewis, R. J., Wang, L., & Prabhu, S. (2014). Being bad in a video game can make us morally sensitive. *Cyberpsychology, Behavior, and Social Networking, 17(*8), 499-504.

Harris, P. A., Taylor, R., Thielke, R., Payne, J., Gonzalez, N., Conde, J. G. (2009). Research electronic data capture (REDCap) - A metadata-driven methodology and workflow process for providing translational research informatics support. *Journal of Biomedical Informatics, 42*(2), 377-81.

Hoffman, E., McCabe, K., & Smith, V. L. (1996). Social distance and other-regarding behavior in dictator games. *The American Economic Review*, *86*(3), 653-660.

Hollingdale, J., & Greitemeyer, T. (2013). The changing face of aggression: The effect of personalized avatars in a violent video game on levels of aggressive behavior. *Journal of Applied Social Psychology*, *43*(9), 1862-1868.

Hughes, C. M. (2015). A measure of social behavior in team-based, multiplayer online games: The Sociality in Multiplayer Online Games Scale (Unpublished master's thesis). Virginia Commonwealth University, Virginia.

Joinson, A. N. (2001). Self□disclosure in computer□mediated communication: The role of self□awareness and visual anonymity. *European Journal of Social Psychology*, *31*(2), 177-192.

Joinson, A. (1999). Social desirability, anonymity, and internet-based questionnaires. *Behavior Research Methods, Instruments, & Computers*, *31*(3), 433-438.

Judge, T. A., Bono, J. E., Ilies, R., & Gerhardt, M. W. (2002). Personality and leadership: a qualitative and quantitative review. *Journal of Applied Psychology, 87*(4), 765-780.

Kavussanu, M., & Boardley, I. D. (2009). The Prosocial and Antisocial Behavior in Sport Scale. *Journal of Sport & Exercise Psychology*, *31*(1), 97-117.

Kavussanu, M., Seal, A. R., & Phillips, D. R. (2006). Observed prosocial and antisocial behaviors in male soccer teams: Age differences across adolescence and the role of motivational variables. *Journal of Applied Sport Psychology, 18*(4), 326-344.

Kiesler, D. J. (1983). The 1982 interpersonal circle: A taxonomy for complementarity in human transactions. *Psychological Review*, *90*(3), 185-214.

Kiesler, S., Siegel, J., & McGuire, T. W. (1984). Social psychological aspects of computer-mediated communication. *American Psychologist*, *39*(10).

Kowert, R., Vogelgesang, J., Festl, R., & Quandt, T. (2015). Psychosocial causes and consequences of online video game play. *Computers in Human Behavior, 45*, 51-58.

Lenhart, A., Kahne, J., Middaugh, E., Macgill, A. R., Evans, C., & Vitak, J. (2008). Teens, video games, and civics: Teens' gaming experiences are diverse and include significant social interaction and civic engagement. *Pew Internet & American Life Project*.

Lewis, M. L., Weber, R., & Bowman, N. D. (2008). "They may be pixels, but they're my pixels:" Developing a metric of character attachment in role-playing video games. *CyberPsychology & Behavior*, *11*(4), 515-518.

Li, D. D., Liau, A., & Khoo, A. (2013). Player-avatar identification: Concepts and measurements. *Computers in Human Behavior, 29*(1), 257-263.

Lieberman, J. D., Solomon, S., Greenberg, J., & McGregor, H. A. (1999). A hot new way to measure aggression: Hot sauce allocation. *Aggressive Behavior,,25*(5), 331-348.

MacManus, Christopher (October 12, 2012). League of Legends the world's 'most played video game'. *CNET. CBS Interactive*. Retrieved from <http://news.cnet.com/8301-17938_105-57531578-1/league-of-legends-the-worlds-most-played-video-game/>.

Masten, C. L., Morelli, S. A., & Eisenberger, N. I. (2011). An fMRI investigation of empathy for 'social pain'and subsequent prosocial behavior. *Neuroimage*, *55*(1), 381-388.

Midha, V., & Nandedkar, A. (2012). Impact of similarity between avatar and their users on their perceived identifiability: Evidence from virtual teams in Second Life platform. *Computers in Human Behavior, 28*(3), 929-932.

Ng, B. D., & Weimer-Hastings, P. (2005). Addiction to the internet and online gaming. *Cyberpsychology & Behavior, 8,* 110-113.

Olthof, T., Goossens, F. A., Vermande, M. M., Aleva, E. A., & van der Meulen, M. (2011). Bullying as strategic behavior: Relations with desired and acquired dominance in the peer group. *Journal of School Psychology, 49*(3), 339-359.

Pereira, C. (October 18, 2013). League of Legends infographic highlights eye-popping numbers. *IGN.* Retrieved from < http://www.ign.com/articles/2013/10/18/league-of-legends-infographic-highlights-eye-popping-numbers>.

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.

Ridgeway, C., & Diekema, D. (1989). Dominance and collective hierarchy formation in male and female task groups. *American Sociological Review, 54,* 79-93.

Tabachnick, B. G., & Fidell, L. S. (2001). Using multivariate statistics.

Tani, F., Greenman, P. S., Schneider, B. H., & Fregoso, M. (2003). Bullying and the Big Five: A study of childhood personality and participant roles in bullying incidents. *School Psychology International, 24*(2), 131-146.

Trapnell, P. D., & Wiggins, J. S. (1990). Extension of the Interpersonal Adjective Scales to include the Big Five dimensions of personality. *Journal of Personality and Social Psychology*, *59*(4).

Vorderer, P., & Bryant, J. (Eds.). (2012). *Playing video games: Motives, responses, and consequences*. New York: Routledge.

Weinstein, N., Deci, E. L., & Ryan, R. M. (2011). Motivational determinants of integrating positive and negative past identities. *Journal of Personality and Social Psychology, 100*(3), 527-544.

Whitaker, J. L., & Bushman, B. J. (2012). "Remain Calm. Be Kind." Effects of Relaxing Video Games on Aggressive and Prosocial Behavior. *Social Psychological and Personality Science, 3*(1), 88-92.

Yang, G. S., Huesmann, L. R., & Bushman, B. J. (2014). Effects of playing a violent video games as male versus female avatar on subsequent aggression in male and female players. *Aggressive Behavior, 40*, 437-541.

Ybarra, M. L., Diener-West, M., & Leaf, P. J. (2007). Examining the overlap in Internet harassment and school bullying: Implications for school intervention.*Journal of Adolescent Health*, *41*(6), S42-S50.

Yee, N., Ducheneaut, N., Nelson, L., & Likarish, P. (2011, May). Introverted elves & conscientious gnomes: the expression of personality in world of warcraft. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (pp. 753-762). Austin, TX.

Appendix A

Behaviors in League of Legends Identified by Focus Groups

Dimension (Behavior)	Definition
Instalocking	An individual enters Champion Select and immediately selects his or her role, without cooperating or consulting his or her teammates. (In Draft Mode, “lock in” can refer to selecting a champion without compromise, even if the player cannot yet click “Lock In.”)
Trolling	An individual intentionally makes the game unpleasant for his teammates.
Role Choice	An individual’s choice to play active, dominant, high damage output roles, or passive, utility-oriented roles.
Leadership	An individual’s choice to “call the shots” or follow the commands of others.
Autonomy/Cooperation	An individual’s level of autonomy in game, as determined by their tendency to follow the team’s strategy or to proceed with their own agenda.
Teaching	An individual’s tendency to share knowledge with other players in order to help improve the others’ gameplay.
Resource Stealing	The tendency for an individual to forfeit the credit for the kill of a champion, a buff, or a minion/monster, and thereby forfeits gold and experience.
Resource Forfeiting	The tendency for an individual to forfeit the credit for the kill of a champion, a buff, or a minion/monster, and thereby forfeits gold and experience.
Raging	The tendency to express excessive verbal aggression towards other players.
Enemy Support	The tendency for an individual to express sympathy or support for his enemies.
Building Positive Rapport	The tendency for an individual to partake in rapport-building behaviors in chat.
Post-game Reports	When an individual gives “honor” to other players at the end of the match, or reports players. “Honors” are recognition for teamwork, friendliness, and helpfulness in game. “Reports” are documented notes of a player’s bad behavior, which are sent to the Game Tribunal for review, and can result in punishment.

Appendix B

SMOG-77

League of Legends Self-Report of Your Gaming Behavior

Your Experience in Online Gaming
How frequently would you estimate you have played League of Legends? ____ # of sessions per week
For how long would you estimate that you have spent online playing League of Legends? ____ # hours per week
How frequently would you estimate you have played all different types of online games? ____ # of times per week
For how long would you estimate that you have played all different types of online games? ____ # hours per week
What is your ranking in League of Legends?

a) I am unranked
b) Bronze V – Bronze III
c) Bronze II – Bronze I
d) Silver V – Silver III
e) Silver II – Silver I
f) Gold V – Gold III
g) Gold II – Gold I
h) Platinum V – Platinum III
i) Platinum II – Platinum I
j) Diamond V – Diamond III
k) Diamond II – Diamond I
l) Challenger

How long have you been playing League of Legends? ____ years ____ months

Directions: For each item below, please report the frequency that you perform the behavior described in the item. Use the following ratings:

0=Never do it (Never)
1=Do it rarely (Rarely)
2=Do it sometimes (Sometimes)
3=Do it fairly often (Fairly Often)
5=Do it often (Often)
6=Do it very often (Very Often)
7=Do it always (Always)

___ “I select/lock in my champion immediately during Champion Select rather than call the champion in the chat box.”
___ “I consult my teammates during Champion Select before I select/lock in my own preference.”
___“If I have selected/locked in my champion, it does not matter who called what role in the chat box.”
___ “I act cooperatively during Champion Select.”
___ “If I want to play a particular role or champion, I do not compromise my choice with my team.”
___ “Even if I want to play a particular role or champion, I cooperate with my team more than play my preference.”

___“I Instalock.”

___“I intentionally make the game more difficult for my teammates.”
___“I intentionally make the game unpleasant for my teammates.”
___“I have intentionally performed poorly in game.”
___“I have fun even if it hurts my team’s chance at winning.”
___“I enjoy making the game suck for my teammates.”
___“I have fun trolling.”
___“I troll.”

___“I play carry-type roles”
___“I play supportive roles.”
___“I carry my team.”
___“I avoid carry roles.”
___“I play with high damage output.”
___“I play to utility-oriented champions.”

___“I call the shots for my team.”
___“I follow the commands of my teammates”
___“I take a leadership role in my team.”
___“I follow the calls of my teammates.”
___“If I do not have an objective at the moment, I ask my teammates what I should do.”
___“If my team doesn’t have an objective at the moment, I make the call for the next step.”

___“If my team makes a call I don’t agree with, I do my own thing.”
___“I am an autonomous player”
___ “I follow my own agenda.”
___“I rely more on my ability as an individual player than the power of team unity.”
___“I rely more on my ability as an individual player than the power of cooperation.”
___“I rely more on cooperation than my individual skill.”
___“I rely more on team unity than my individual skill.”
___“If my teammates make a call I don’t agree with, I’ll follow it anyway.”
___“I am a team-oriented player.”
___ “I am a cooperative player.”

___“If I am more skilled or knowledgeable than my teammates, I share my knowledge with them.”
___“If I see a teammate making mistakes, I tell them how to correct it.”
___“If I am a stronger player than my peers, I try to help the weaker players improve their gameplay.”
___“I do not teach other players how to improve.”
___“I take up the responsibility to help other players improve.”
___“I don’t bother with helping other players to improve their gameplay.”

___“If I need a buff, I’ll just take it from the Jungle.”
___“I intentionally steal kills from my teammates.”
___“If I need more kills, I take them from my teammates without permission.”
___“I only take the kills I need.”
___“I ask permission before taking a buff from my Jungler”
___“I am careful not to take resources from those who need it.”

___“I forfeit kills to my teammates, if they need it.”
___“I will not clear a wave of minions, if one of my teammates would benefit more from it.”
___“I try to make sure that my teammates get enough resources.”
___“I will clear a wave of minions, even if the gold would better benefit one of my teammates.”
___“I do not hand over kills to my teammates.”
___“As the Jungler, I give buffs to my teammates even when I don’t want to.” (If you do not Jungle, please answer how you feel a Jungler should answer.)

___"If I am frustrated with my teammates, I reproach them in the chat box."
___"I get verbally aggressive with other players."
___"I rage during games."
___"Even if I am angry at my teammates, I do not show them my anger."
___"I have been described as a toxic player."
___"I refrain from comments that express negative emotion in the chat box."

___"If someone from the enemy team makes a good play, I congratulate his or her success."
___"If someone from the enemy team AFKs, I express my condolences."
___"If my opponents behaved honorably, I Honor them at the end of the match." [this question is also in the "Post-Game Report" section.]
___"I am not friendly towards the enemy team"
___ "I treat my opponent as an antagonist."
___ "I do not build rapport with my opponents."

___"I encourage my teammates during gameplay."
___"If my teammates make a good play, I congratulate them."
___"If my teammates are having a poor play experience, I express my sympathy to them."
___"I try to build a sense of team unity in the chat box."
___"I don't bother with building team rapport."
___"I focus more on in-game play than rapport-building in the chat box."

___"If my teammates behaved honorably, I Honor them at the end of the match."
___"If one of the players is violating the Summoner's Code, I report them at the end of the match."
___"If I plan to report a player, I try to encourage other players to report him or her, too."
___"I do not bother with Honoring or reporting other players."

Appendix C

SMOG-11

Your Experience with Multiplayer Online Gaming:

How frequently would you estimate you play all different types of multiplayer online games?
____ # of times per week

For how long would you estimate that you play all different types of multiplayer online games?
____ # hours per week

Directions: For each item below, please report the frequency that you perform the behavior described in the item. Use the following ratings:

0 – Never
1 – Rarely
2 – Infrequent
3 – Sometimes
4 – Fairly often
5 - Often
6 – Very often
7 – Always

___“I intentionally make the game unpleasant for my teammates.”
___“I have intentionally performed poorly in game.”
___“I enjoy making the game suck for my teammates.”
___”I get verbally aggressive with other players.”
___“I have been described as a toxic player.”
___“If I am more skilled or knowledgeable than my teammates, I share my knowledge with them.”
___“If I am a stronger player than my peers, I try to help the weaker players improve their gameplay.”
___“I take up the responsibility to help other players improve.”
___“I encourage my teammates during gameplay.”
___“If my teammates make a good play, I congratulate them.”
___“I try to build a sense of team unity in chat.”

Appendix D

SMOG-6

Your Experience with Multiplayer Online Gaming:

How frequently would you estimate you play all different types of multiplayer online games?
____ # of times per week

For how long would you estimate that you play all different types of multiplayer online games?
____ # hours per week

Directions: For each item below, please report the frequency that you perform the behavior described in the item. Use the following ratings:

0 – Never
1 – Rarely
2 – Infrequent
3 – Sometimes
4 – Fairly often
5 - Often
6 – Very often
7 – Always

___"I have intentionally performed poorly in game."
___"I enjoy making the game suck for my teammates."
___"I get verbally aggressive with other players."
___"I take up the responsibility to help other players improve."
___"I encourage my teammates during gameplay."
___"I try to build a sense of team unity in chat."

Appendix E

*Norms for Full-Sample Participants (*N *= 354) by Age, Gender, and Ethnicity*

	n	%	*Min.*	*Max.*	*Mean*	*SD*
Age	-	-	18	50	21.17	5.62
Gender	-	-	-	-	-	-
Male	239	67.5	-	-	-	-
Female	103	29.1	-	-	-	-
Transgender	3	.8	-	-	-	-
Rather not say	9	2.6	-	-	-	-
Ethnicity	-	-	-	-	-	-
Non-Hispanic White or Euro-American	206	59.0	-	-	-	-
East Asian or Asian-American	40	11.3	-	-	-	-
Latino/Latina or Hispanic American	19	5.4	-	-	-	-
African-American , Afro-Caribbean, or Black	25	7.1	-	-	-	-
South-Asian or Indian-American	12	3.4	-	-	-	-
Native-American or Alaska Native	2	.6	-	-	-	-
Middle Eastern or Arab-American	4	1.1	-	-	-	-
Other	28	7.9	-	-	-	-
Rather not say	18	5.1	-	-	-	-

Vita

Chelsea Marie Hughes is pursuing her doctoral degree in Psychology at Virginia Commonwealth University. She was born on September 9, 1991 in Covington, Louisiana, and is a citizen of the United States. She received her B.A. in Psychology from East Carolina University, graduating in three years, *Magna Cum Laude* from the inaugural class of the ECU Honors College. Immediately after graduation, Chelsea began her graduate career at VCU. In her doctoral program, she works under Dr. Everett Worthington and is an active member of the Positive Psychology Research Group. Chelsea's own research focuses on communication, particularly social interaction in online gaming.