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Author(s): Şengün, Sercan; Santos, Joao M.; Salminen, Joni; Jung, Soon-gyo; Jansen, Bernard J.

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Do players communicate differently depending on the champion played? Exploring the Proteus effect in League of Legends

Sercan Şengün[5], Joao M. Santos[3], Joni Salminen[1, 2], Soon-gyo Jung[1], Bernard J. Jansen*[, 1, 4]

[1] Qatar Computing Research Institute, Hamad Bin Khalifa University, Doha, Qatar
[2] University of Vaasa, Vaasa, Finland
[3] Centre for Research and Studies in Sociology (CIES-Iscte), Iscte - Instituto Universitário de Lisboa, Lisbon, Portugal
[4] College of Information Sciences and Technology, The Pennsylvania State University, USA
[5] Creative Technologies, Wonsook Kim College of Fine Arts, Illinois State University, Normal IL., USA

ssengun@ilstu.edu, joao_marques_santos@iscte-iul.pt, jsalminen@hbku.edu.qa, sjung@hbku.edu.qa, jjansen@acm.org

* - corresponding author

Abstract

We investigate how the Proteus effect, players changing their way of communication based on characters they play with, is associated with players' champion usage in the popular online game League of Legends, where champions are the characters that the players control. First, we create two sets of variables: (a) *objective champion characteristics* based on information from the game developer, which we further enrich by semiotic coding, and (b) *subjective champion characteristics* based on crowdsourced opinions about the champions. Then, we analyze 13.6 million in-game chat messages to measure whether the players' vocality (character counts of messages), valence (negative versus positive scores of language use), and toxicity (frequency of toxic word usage) change depending on the characteristics of the champions they employ. We find that champions' body type, role, and gender are associated with players' higher vocality, toxicity, and negative valence. We also find that the players' communication significantly changes in terms of toxicity and valence when they play between different champions. We discuss our methodology and results in detail and propose design directions based on them and other implications.

Keywords: games, toxicity, vocality, valence, League of Legends, Proteus effect

1 Introduction

The Proteus effect is defined as "*users who are deindividuated in online environments [adhering] to a new identity that is inferred from their avatars*" and "*users in online environments [conforming] to the expectations and stereotypes of the identity of their avatars*" (Yee et al., 2009, p. 274). In simpler terms, the Proteus effect is a tendency for people to be affected by their digital representations. This study explores if and how the Proteus effect manifests among the *League of Legends* players. More particularly, we investigate if players' in-game messaging style varies by their champion (i.e., the game character with which a player chooses to play), as a single player can play multiple champions. We approach the in-game chat behaviors through the lenses of vocality, valence, and toxicity, as these are crucial online communication behaviors (Abdalla Mikhaeil & Baskerville, 2019; Beres et al., 2021; H. S. Choi et al., 2018; Tan, 2020; J. Tang et al., 2021; Xi et al., 2021).

League of Legends (LoL)—a multiplayer online battle arena (MOBA) game first published by Riot Games in 2009—is reported to be the "most played video game" in the world for multiple years, from 2012 (MacManus, 2012) and all the way through to 2019 (Messner, 2019). In the game, two teams of five players battle on a map after each player chooses a champion from a rich roster (155 champions as of April 2021; 136 champions[1] at the time the data was collected) of avatars[2] with different designs and abilities. The designs of LoL champions seem to be inspired by many different sources over the years, including mythological creatures (Park & Seo, 2019), real-world ethnic identities (Sengün, Salminen, Mawhorter, et al., 2019), and, perhaps unsurprisingly, social stereotypes (Gao et al., 2017).

[1] Aatrox, Ahri, Akali, Alistar, Amumu, Anivia, Annie, Ashe, Aurelion Sol, Azir, Bard, Blitzcrank, Brand, Braum, Caitlyn, Camille, Cassiopeia, Cho'gath, Corki, Darius, Diana, Dr.Mundo, Draven, Ekko, Elise, Evelynn, Ezreal, Fiddlesticks, Fiora, Fizz, Galio, Gangplank, Garen, Gnar, Gragas, Graves, Hecarim, Heimerdinger, Illaoi, Irelia, Ivern, Janna, Jarvan IV, Jax, Jayce, Jhin, Jinx, Kalista, Karma, Karthus, Kassadin, Katarina, Kayle, Kennen, Kha'zix, Kindred, Kled, Kog'maw, Leblanc, Lee Sin, Leona, Lissandra, Lucian, Lulu, Lux, Malphite, Malzahar, Maokai, Master Yi, Miss Fortune, Mordekaiser, Morgana, Nami, Nasus, Nautilus, Nidalee, Nocturne, Nunu & Willump, Olaf, Orianna, Pantheon, Poppy, Quinn, Rakan, Rammus, Rek'sai, Renekton, Rengar, Riven, Rumble, Ryze, Sejuani, Shaco, Shen, Shyvana, Singed, Sion, Sivir, Skarner, Sona, Soraka, Swain, Syndra, Tahm Kench, Taliyah, Talon, Taric, Teemo, Thresh, Tristana, Trundle, Tryndamere, Twisted Fate, Twitch, Udyr, Urgot, Varus, Vayne, Veigar, Vel'koz, VI, Viktor, Vladimir, Volibear, Warwick, Vukong, Xayah, Xerath, Xin Zhao, Yasuo, Yorick, Zac, Zed, Ziggs, Zilean, and Zyra.

[2] Although we realize that some nuance might exist contextually, for the purposes of this study, we use the terms champion, avatar, and character interchangeably.

Due to its global popularity and the variability of its characters, LoL provides an interesting virtual testbed for social science research. Previously, LoL champions have been examined from popularity and usage perspectives, such as champion features (Zhang et al., 2017) and powers (Poeller et al., 2020) affecting their adoption by players. Additionally, behaviors of LoL players have been examined through the general lenses of player skill levels and expertise (Ding et al., 2018; Donaldson, 2017), team performance (Kim et al., 2017; Kou & Gui, 2014), and strategy-making (Lee & Ramler, 2017).

However, to the best of our knowledge, prior research has not explored how players' communication behaviors change depending on the champion they play, an expression of the Proteus effect. To explore this possible change, we use in-game chats to look at several indicators, including acting more vocal (i.e., writing longer messages), acting more toxic (i.e., frequently using toxic words), and showing positive or negative valence—a form of sentiment analysis of a text that shows the "*affectual state of the author*" (see Mohammad, 2016, p. 201 for details), as these are indications of the Proteus effect on player communication. In turn, communication behaviors such as increased toxicity and negativity can impact players' well-being in MOBAs (Sengün, Salminen, Jung, et al., 2019).

To investigate these matters in greater depth, we create several groups of champion characteristics, including a set of (a) *objective champion characteristics* that originate from the game developer's information about each champion, which we enrich via a procedure of semiotic coding (Abdalla Mikhaeil & Baskerville, 2019), and (b) *subjective champion characteristics* that are based on previous social psychology models (Kaye, Kowert, et al., 2017) and rated through crowdsourcing for each champion. Ultimately, we want to see if these sets of characteristics predict how players behave in their game communication, which would provide greater insight concerning the Proteus effect. This is the motivation for our research. To this end, we pose the following research questions (RQs):

- **RQ1:** How do objective and subjective champion characteristics affect players' *vocality*?
- **RQ2:** How do objective and subjective champion characteristics affect players' *valence*?
- **RQ3:** How do objective and subjective champion characteristics affect players' *toxicity*?

We focus specifically on the three aspects of vocality, valence, and toxicity, as these are primary aspects of textual communication analysis. If the Proteus effect actually occurs in the LoL domain, one would certainly expect the effect to manifest itself in these three aspects of communication. Although perhaps there are other communication modes to address, we consider these aspects of communication to be the most impactful in terms of the effect on the online community.

To further investigate the Proteus effect, we also observe the players' behaviors as they play with different champions (i.e., in LoL, a player may use different champions for different sessions). Apart from predicting vocality, toxicity, and valence based on champion characteristics, we want to investigate whether the players change their communication behaviors when changing the champion they play with, which would further confirm/refute the presence of the Proteus effect, providing enhanced insights concerning the Proteus effect in online gaming. Therefore, our final RQ is

- **RQ4:** Do the levels of vocality, valence, and toxicity change when a player changes champions?

These research questions are important because, if the Proteus effect is prevalent, this research will show direct behavioral outcomes, specifically in player communications, that affect the online gaming domains and other online community platforms that utilize avatars. Additionally, to our knowledge, this is the first work in LoL that examines the Proteus effect during periods of players changing avatars, strengthening the analysis of the Proteus effect while controlling for specific users of these champions. Finally, unlike some prior work, this research reports analysis of actual players' (as compared to research participants) behaviors in their own gameplay environment engaging in a commercially published game using commercially designed avatars (as opposed to a game produced for specific research purposes), strengthening the literature concerning the Proteus effect via new methodological approaches.

In the next section, we review related work on the Proteus effect as well as vocality, valence, and toxicity in games. After this, we explain how the data was collected and how we constructed the variables for the analysis. This is followed by the presentation of the results of the statistical analysis.

We then discuss the results, including their implications for game developers and society. We also point out limitations and how they can be addressed in future work. The conclusion summarizes the major takeaways from this study.

2 Related Work

2.1 Proteus Effect

The original research by Yee and Bailenson (2007) tested the performance difference in a virtual interpersonal task between conditions when participants are assigned attractive versus less attractive and tall versus short avatars. They found that participants with more attractive avatars behaved more intimately, and those with taller avatars behaved more confidently in online interactions. In a follow-up study, Yee and Bailenson replicated the results and, this time, added the dimension of participants meeting face-to-face after their virtual interactions through avatars. As a result, they found that "*the behavioral changes stemming from the virtual environment transferred to subsequent face-to-face interactions*" (Yee et al., 2009, p. 285).

The implications of the Proteus effect have been researched from the lenses of e-learning environments and opportunities (Blake, 2013; Thorne et al., 2009), virtual work environments (Gilson et al., 2015), and online games (Barnett & Coulson, 2010; Looy et al., 2012). Moreover, the effects of embodiments of different avatars on various social phenomena have been illustrated. For studies investigating the Proteus effect and racial bias, see Groom et al. (2009); for health behaviors, see Fox and Bailenson (2009) and Dascal et al. (2017); and for motivation, see Baylor (2009). Interactions in virtual environments have also been shown to be affected by avatars (Vasalou & Joinson, 2009; Schultze, 2010). In their virtual reality experiment, Banakou *et al.* (2013) display that embodying a child-like body in a virtual environment can result in the overestimation of object sizes and attitude changes, and they conclude that "*altered bodily self-representation can have a spontaneous and significant influence on aspects of perception and behavior*" (p. 12850).

Occasionally, the Proteus effect is discussed in relation to cultural priming (priming from now on for short; Berkowitz, 1984, 1974), which is a phenomenon that occurs when "*people think, act, or feel in a* *manner consistent with situational cues without the intention to do so or the awareness of having done so*" (Peña et al., 2009, p. 839). In an on-screen third-person view experiment, Peña *et al.* (2009) show that the participants using avatars with black robes behaved more aggressively than those using avatars with white robes. The design of the robes in this experiment was based on Klu Klux Klan (KKK) members for black and doctor uniforms for white robes. Peña *et al.* (2009) point out the cultural priming potentials in this experiment, specifically for participants who would be historically familiar with the aggressive connotations of the garment, and generally for most cultures wherein black versus white would be associated with evil versus good. Such cultural priming can become necessary for a study on LoL champions since it was previously argued to have cultural connotations in character design that could affect culture-based interactions between the players (Sengün, Salminen, Jung, et al., 2019; Sengün, Salminen, Mawhorter, et al., 2019). Harrell *et al.* (2021) discuss the different ways that gaming avatars designed based on certain ethnic clues can result in racial ethnic socialization strategies with players from said ethnicities and others.

However, since a priming perspective would require different kinds of data and methodology, in this study, we instead focus on the explicit communication behaviors of vocality, toxicity, and valence of the chosen champions of players. As such, this research adds to the body of work investigating the Proteus effect by a focused study of communication and integration of the priming.

2.2 Toxicity, Valence, and Vocality in League of Legends and Other Online Games

Managing toxic behaviors (Iandoli et al., 2021)—defined as a group of negative behaviors including cyberbullying, griefing (Chesney et al., 2009), mischief, and cheating (Kwak et al., 2015)—in online games is a prevalent and detrimental issue both for the developer companies and gamer communities. Past research highlights several dimensions of tackling toxic behavior in online games, such as predicting and detecting toxic behaviors (Blackburn & Kwak, 2014; Märtens et al., 2015) and using coping strategies (Adinolf & Turkay, 2018). Kordyaka *et al.* (2020) argue that, in online games, "*being unidentifiable is particularly relevant for engaging in toxic behavior due to the influence of negative disinhibition*." This is in line with Hardaker's (2010, p. 215) assertion that online communication "*may encourage a sense of impunity and freedom from being held accountable for inappropriate online* *behaviour*." Paul (2018) asserts that gaming culture is already constructed around meritocracy, and meritocratic norms can be inherently toxic.

LoL historically used flagging, tribunal, and awarding systems to tackle toxic behaviors—players flag the behaviors and chats that they think are toxic; the flagged content is peer-reviewed by other players; players can award honor points to other players whom they think were courteous (Kou & Gui, 2021; Kou & Nardi, 2014). LoL also has several types of matches—specifically normal and ranked ones. Ranked matches form the competitive backbone of LoL esports. Shores *et al.* (2014) find that ranked matches are associated with more toxic behaviors than the normal ones due to their competitive nature. Gao *et al.* (2017) assert that there are gendered differences between play styles and toxicity, and female players are likely to face more toxicity than males.

Although reliance on word lexicons can be challenging (Sengün, Salminen, Mawhorter, et al., 2019; Sengün, Salminen, Jung, et al., 2019), the approach is commonly used for toxicity detection. For example, Märtens and fellow researchers (2015) employ a natural language processing approach to detect profanity in chat logs and classify toxic comments. Kwak and Blackburn (2015) used linguistic analysis techniques on LoL chat data to define phase transition predictors that can predict regular players phasing into toxic players. By looking at the language use of the players, they assert that there are specific chat patterns that toxic players use (e.g., no use of emoticons, no use of apology words, no use of praising words). Stoop and colleagues (2019) developed a machine learning approach to detect the presence of toxic speech early in the conversation.

Valence analysis is a form of sentiment analysis of texts for determining "*feelings from text, in other words, automatically determining valence, emotions, and other affectual states [of the author] from text*" (Mohammad, 2016, p. 201). There are various contemporary methods for valence analysis such as machine learning, fuzzy logic, and statistical methods; however, most valence analyses rely on keyword spotting and dictionaries of affective concepts and lexicons (Shaikh et al., 2007). Valence analysis has previously been used in game research for various purposes, such as predicting social identity construction in massively multiplayer online games (Guegan et al., 2015) and game reviews

(Livingston et al., 2011), as well as chat analysis in LoL (Blackburn & Kwak, 2014; Kokkinakis et al., 2016).

Vocality can be defined as outspokenness, participation, or *making your voice heard* in a cultural (Seiler, 1996) or narrative (Burke, 2016) setting. Kačmárová (2005) asserts that although vocality "*is a defining feature of oral communication*," it can manifest in written communication as "wordiness" and "conversationality," both of which imply using more but also correctly typed words and sentences that are constructed less colloquially. Based on this assertion, we use character count instead of word count to measure vocality in this study.

3 Methodology

3.1 Data Collection and Variable Computations

LoL's developer Riot Games provided the anonymized data for this research, including about one billion lines of chat data with the associated champion, player, and match details. The data was collected from Europe Nordic & East (EUNE) and Europe West (EUW) servers during a timeframe between 2016 and 2017. For analyzing RQs 1–3, we randomly sampled a set of 100,000 chat lines from 136 champions each for a total of 13.6 million chat lines. A summary of our analysis approach is presented in Table 1.

Table 1: Measurements used to address each Research Question (RQ).

RQ	Measurement
Champion characteristics affect a player's vocality	Mean for each champion using the measured the length of each chat line by character count
Champion characteristics affect a player's valence	Means of valence for each champion using the AFINN sentiment analysis Python library that gave us a valence score for each chat line
Champion characteristics affect a player's toxicity	Toxicity value (T) for each champion wherein F is the frequency of toxic words, and U is the word counts of the rest of the messages
Change when a player changes between champions	Within- and between-champion differences for vocality, valence, and toxicity scores using averaged the absolute difference

To analyze toxicity, we used a previously tested word lexicon (constructed and used in Sengün, Salminen, Jung, et al., 2019; Sengün, Salminen, Mawhorter, et al., 2019) and bolstered it with additional sources (Gabriel, 2017/2021; Hauptfleisch, 1993; "List of Ethnic Slurs by Ethnicity," 2021) for a total of 172 toxic words that appear in LoL in-game chats (the dictionary is available from the authors upon request). For each champion, we calculated an F value (i.e., how frequently toxic words appeared in chat when that champion was being played) and a U value (i.e., the count of words in those messages that did not include any toxic term) to come up with a T value (toxicity) between 0 and 1 such as:

Formula 1. The formula for toxicity value (T) for each champion wherein F is the frequency of toxic words, and U is the word count of the rest of the messages.

$$T = \frac{F}{U}$$

To analyze valence, we used a Python library for the AFINN sentiment analysis (Nielsen, 2011), which gave us a valence score for each chat line. We then calculated the means of valence for each champion.

To analyze vocality, we measured the length of each chat line using characters and calculated a mean for each champion.

For RQ4, we first randomly selected a sample set of 1,000 players who have played with more than one champion in the dataset and calculated within- and between-champion differences for toxicity, valence, vocality, and toxicity scores. For each score, we averaged the absolute difference for all combinations of games the player played with the same champion versus games the player played with different champions. When we compared these scores with a t-test for that specific player, we concluded that toxicity and valence vary more between champions than within champions. That is, if the variation of toxicity and valence across games depends on the champion played, this indicates the Proteus effect.

For validation and replication, we sampled five more sets with 1k, 2k, 3k, 4k, and 5k players. All these sets contained unique players who were not sampled in previous sets and followed these rules: (1) The player played with at least two champions; (2) The player played at least two games per champion; and (3) The player typed at least one chat line per game. Replicating our results for each sample set confirmed the significance of our results with consistent effect sizes.

3.2 *Objective and Coding-Based Champion Attributes*

These attributes bring together information either acquired from the objective official LoL champion database[3] or coded by one of the researchers through semiotic analysis (Penn, 2000) of the champion's still images retrieved from the game's website. An exploratory summary of this data is provided in Table 2. Even though there are various images for each champion, the images we used for the analysis were the official images that appear in the champion database as well as on the champion selection screen. Our analysis does not include the different skins of each champion, which can sometimes drastically change the champion's appearance. The semiotic significance rules were created by the whole research team to be objective within the data and were based on previous research around the signifiers of the Proteus effect and toxicity (such as body type, cultural origins, etc., as outlined in the Related Work section).

- **Champion body type:** Each champion was coded either "0" (does not signify) or "1" (signifies) based on whether they signified a human, a monster, an animal, or a mechanical creature. It should be noted here that the signification of a human does not encapsulate just having a humanoid figure but other visual signifiers that associate the champion with human-like behaviors or cultures. A single champion can signify several types at the same time. For example, *Ahri, The Nine-Tailed Fox*[4] signifies a human, an animal, and a monster at the same time.
- **Visual-based aggressiveness signifiers (VBAS):** Each champion was coded either "0" (no) or "1" (yes) for the following questions: Do they hold a weapon? Do they smile? Do they show teeth? For the first question, we factored in only the unsheathed weapons held in hand and not the existence of weapon straps and holders on the body. We also answered the question as "1" if the front limbs of the champion resemble or contain a natural weapon (such as claws, spikes, etc.). For the second question, we factored in all smile types (closed, upper, and broad) (Otta et

[3] https://na.leagueoflegends.com/en-us/champions/
[4] https://na.leagueoflegends.com/en-us/champions/ahri/

al., 1996) without factoring in the perception of stimulus (e.g., smirking versus smiling; both were coded as "1"). For the third question, any number of teeth showing was coded as "1".

- **Cultural origin:** Each champion was coded either as "0" (does not signify) or "1" (signifies) based on whether they signified a specific real-world culture or a fantasy-based cultural phenomenon. In some cases, some fantasy-based cultural phenomena can also be attributed to specific real-world cultures (e.g., vampires and werewolves can be attributed to different European folklore, etc.); however, to determine real-world culture signification, we looked for more specificity and purposeful attribution.
- **Gender:** The official LoL champion database attributes a pronoun to each champion. We assigned the male, female, and other genders to champions based on the "he," "she," and "it" pronouns used, respectively.
- **Role:** In the official LoL champion database, each champion has one of the six roles assigned to them: assassin, fighter, mage, marksman, tank, or support.
- **Difficulty:** Finally, in the official LoL champion database, each champion also has a difficulty value assigned to them between 1 and 3, with 1 being the easiest to play and 3 being the hardest to play.

The results of the coding are presented in Table 2, showing that Human and Monster are the most common body types. Most characters have a weapon, most characters are male, and the roles are fairly balanced.

Table 2: An exploratory summary for objective and coding-based champion attributes.

Attribute	Percentage
Champion Body Type: Human	*n*=96 (72.8%)
Champion Body Type: Monster	*n*=71 (52.2%)
Champion Body Type: Animal	*n*=24 (17.7%)
Champion Body Type: Mechanical	*n*=7 (5.2%)
VBAS: Has Weapon	*n*=105 (77.2%)
VBAS: Has Smile	*n*=40 (29.4%)
VBAS: Shows Teeth	*n*=57 (41.9%)
Cultural Origin: Specific	*n*=27 (19.9%)
Cultural Origin: Fantasy	*n*=20 (14.7%)
Gender: Male	*n*=84 (61.8%)
Gender: Female	*n*=46 (33.8%)

Attribute	Percentage
Gender: Other	*n*=6 (4.4%)
Role: Assassin	*n*=15 (11.0%)
Role: Fighter	*n*=39 (28.7%)
Role: Mage	*n*=30 (22.1%)
Role: Marksman	*n*=21 (15.4%)
Role: Support	*n*=13 (9.6%)
Role: Tank	*n*=18 (13.2%)
Difficulty: 1	*n*=18 (13.2%)
Difficulty: 2	*n*=89 (65.4%)
Difficulty: 3	*n*=29 (21.3%)

3.3 Subjective Champion Attributes

Subjective champion attributes indicate what people perceive the champion to be like (e.g., aggressive or friendly). We reviewed the literature on social psychology (Dion et al., 1972; Ekman, 1999; Epley et al., 2007; Gosling et al., 2003; Levant, 2011; McNeil, 1959; Sidanius et al., 2017; Williams, 1973) and chose to include a range of attributes typically operationalized in person-to-person interaction (see Table 3). Investigating if these attributes affect how a champion is played addresses the subjective dimension in RQs 1–3.

Table 3: Subjective champion attributes.

Attribute	Source	Emotions	Physical appearance	Personality	Behavior
angry	Ekman's six basic emotions (Ekman, 1999)	x			
surprised	Ekman's six basic emotions (Ekman, 1999)	x			
disgusted	Ekman's six basic emotions (Ekman, 1999)	x			
enjoying	Ekman's six basic emotions (Ekman, 1999)	x			
afraid	Ekman's six basic emotions (Ekman, 1999)	x			
sad	Ekman's six basic emotions (Ekman, 1999)	x			
realistic	Anthropomorphism (Epley et al., 2007)		x		

Attribute	Source	Emotions	Physical appearance	Personality	Behavior
comical*	Anthropomorphism (Epley et al., 2007)		x		
masculine	Masculinity (Levant, 2011)		x		
feminine*	Masculinity (Levant, 2011)		x		
handsome / beautiful	Attractiveness (Dion et al., 1972)		x		
ugly*	Attractiveness (Dion et al., 1972)		x		
extravert (social, talkative)	Big five (Gosling et al., 2003)			x	
open (receptive, imaginative)	Big five (Gosling et al., 2003)			x	
conscientious (thoughtful, organized)	Big five (Gosling et al., 2003)			x	
agreeable (trusting, kind)	Big five (Gosling et al., 2003)			x	
neurotic (moody, unstable)	Big five (Gosling et al., 2003)			x	
aggressive	Aggression (McNeil, 1959)				x
friendly*	Aggression (McNeil, 1959)				x
powerful	Dominance (Sidanius et al., 2017)				x
submissive*	Dominance (Sidanius et al., 2017)				x
selfish	Egoism (Williams, 1973)				x
helpful*	Egoism (Williams, 1973)				x

Note: indicators marked with asterisk (*) were reversed when calculating the attribute's score.

A crowdsourced task was carried out to collect subjective ratings based on champions' profile pictures (see example in Figure 1).

(a)	(b)

Figure 1: Examples of champion pictures used for obtaining subjective ratings. Aatrox **(a)** would likely rank high on attributes such as anthropomorphism and aggression as the character seems human-like and menacing, whereas Teemo **(b)** would rank low as the character portrays an animal that seems happy.

This involved showing crowd-workers a champion's picture (the same picture that was used in the semiotic analysis above) and asking their opinions of the champion. The general instruction given was: "Evaluate how the video game character appears to you based on their picture. There are no right or wrong answers—please give your honest opinion to help our study produce valid results. Thank you!". The specific statements were "Looks like this character is **[angry]**.", where **[angry]** represents one of the six emotions; and "This character seems **[masculine]**.", where **[masculine]** refers to physical appearance, personality, or behavior. The answer options followed the five-point Likert scale (1 = Strongly disagree, 5 = Strongly agree). All 136 champions were rated by 15 crowd-workers, and the subjective ratings were calculated as the mean of the given ratings.

Table 4 shows the descriptive statistics for these ratings, with Powerful, Aggression, and Masculine being the highest-rated subjective champion attributes.

Table 4: Descriptive statistics for the subjective champion attributes.

Attribute	M	SD	Min	Max
Powerful	3.997	0.476	2.267	4.933
Aggression	3.502	0.700	1.270	4.600
Masculine	3.462	1.237	1.067	5.000
Angry	3.386	0.840	1.333	4.933

Attribute	M	SD	Min	Max
Helpful	3.341	0.444	2.333	4.267
Disgusted	3.244	0.684	1.600	4.733
Neurotic	3.188	0.642	1.733	4.400
Handsome	3.107	0.874	1.467	4.600
Selfish	2.955	0.456	1.800	3.929
Realistic	2.820	0.532	1.600	4.067
Enjoying	2.800	0.624	1.667	4.667
Conscientious	2.793	0.485	1.733	3.867
Ugly	2.776	0.841	1.200	4.600
Open	2.764	0.531	1.667	4.333
Agreeable	2.730	0.648	1.267	4.867
Extrovert	2.672	0.542	1.800	4.267
Friendly	2.619	0.728	1.400	5.000
Feminine	2.562	1.273	1.143	5.000
Comical	2.412	0.516	1.533	4.133
Submissive	2.224	0.435	1.200	3.533
Surprised	2.207	0.306	1.467	2.933
Sad	2.167	0.454	1.267	4.800
Afraid	2.054	0.373	1.333	4.067

4 Results

4.1 Statistical Procedure

To answer RQs 1–3, a hierarchical regression (Hair et al., 2014) was conducted, where the first step included the objective champion characteristics, and the second step added the subjective champion characteristics. Comparison of the R^2 changes allowed us to determine whether one of these sets of variables had more predictive power than the other. For interpretative purposes, the subsequent section will focus on the full model.

Before proceeding with the final regression, variance inflation factor (VIF) values were scanned to ascertain possible multicollinearity between the variables (Montgomery et al., 2021). Multicollinearity is the model's correlation between predictors (i.e., independent variables); multicollinearity adversely affects regression results. The VIF values estimate how much the variance of a regression coefficient is inflated due to multicollinearity in the model. Several occurrences were noted and addressed. Champion Gender (VIF = 10.021) was highly correlated with Masculinity (VIF = 10.540). As such, Masculinity was removed from the analysis. Additionally, Angry (VIF = 11.985), Disgusted (VIF = 10.440), and Aggression (VIF = 15.981) were also highly correlated. Due to conceptual overlap, it was attempted to create an Anger-Aggression variable comprised of the mean of both Angry and Aggression. However, this created a new issue as it was highly and negatively correlated with Agreeableness, with a VIF of 10.145. As such, it became necessary to remove both Anger and Aggression entirely. These actions resolved all multicollinearity issues from the model. In addition, we also attempted interacting the physical characteristics of the champion, such as gender (Kaye, Kowert, et al., 2017), with the various champion roles to determine if the impacts on toxicity, valence, or vocality, varied by role. This yielded 150 interaction terms in total, of which nearly all exhibited non-significant results. In the interest of space and brevity, we opted to remove these interaction terms from the final analysis as they only indicated that the findings were consistent across roles. As such, we do not report the 150 non-significant interactions results.

A final pre-processing step was conducted, which was multiplying the toxicity scores by 100. This was simply to facilitate reading the unstandardized coefficients, which would otherwise be rounded down to zero since toxicity is measured in small absolute values.

4.2 RQ1: How Do Objective and Subjective Champion Attributes Affect a Player's Vocality?

The model regarding vocality is shown in Table 5.

Table 5: Hierarchical regression for vocality, with unstandardized coefficients and standard errors. Significant results in **bold**.

Variable	Model I	Model II
Champion Body Type: Human	0.041 (0.067)	0.061 (0.072)
Champion Body Type: Monster	**0.129* (0.059)**	**0.160* (0.067)**
Champion Body Type: Animal	-0.070 (0.065)	-0.027 (0.070)
Champion Body Type: Mechanical	0.131 (0.110)	0.173 (0.115)
VBAS: Has weapon	0.045 (0.059)	0.016 (0.064)
VBAS: Has smile	-0.005 (0.051)	0.089 (0.062)
VBAS: Shows teeth	-0.053 (0.052)	-0.078 (0.067)
Cultural Origin (Specific)	-0.023 (0.063)	-0.023 (0.066)
Cultural Origin (Fantasy)	0.096 (0.064)	0.109 (0.066)

Variable	Model I	Model II
Gender (Male)	-0.051	-0.096
	(0.050)	(0.063)
Gender (Other)	-0.058	-0.090
	(0.126)	(0.137)
Role (Assassin)	**-0.243****	**-0.208***
	(0.092)	**(0.099)**
Role (Fighter)	0.046	0.047
	(0.074)	(0.079)
Role (Mage)	0.131	0.151
	(0.077)	(0.082)
Role (Marksman)	**0.171***	**0.213***
	(0.084)	**(0.089)**
Role (Support)	0.054	0.099
	(0.091)	(0.093)
Difficulty	0.019	0.023
	(0.040)	(0.045)
Surprised		0.025
		(0.090)
Disgusted		0.135
		(0.073)
Enjoying		0.028
		(0.069)
Afraid		-0.051
		(0.098)
Sad		0.044
		(0.074)
Immersion		0.003
		(0.097)
Attractiveness		-0.038
		(0.059)
Extrovert		-0.032
		(0.101)
Open		-0.032
		(0.111)
Conscientious		0.059
		(0.082)
Agreeable		0.028
		(0.088)
Neurotic		-0.074
		(0.069)
Dominance		0.137
		(0.108)
Egoism		-0.005
		(0.101)
R^2	0.297	0.391
R^2 Δ	0.297	0.094

Notes: *** p < 0.001; ** p < 0.01; * p < 0.05. The table shows the unstandardized coefficients, with standard errors in parenthesis.

The models for vocality exhibit the lowest levels of predictive power. The baseline model, with only objective features, explains 29.7% of the variance, and this increases slightly to 39.1% with the inclusion of subjective features, which is, however, a non-significant change ($F(14, 104) = 1.150$, $p = .325$). Additionally, similar to what occurred with toxicity and explained below, none of the subjective features were significant, indicating that these are not relevant predictors of vocality.

Only a few objective characteristics were found to have significant effects. Monster champions were associated with higher degrees of vocality ($b = 0.160$, $p < .05$). Roles were yet the strongest predictors, but to a lesser degree to what occurred with the other dependent variables. Assassins exhibited lower degrees of vocality ($b = -0.208$, $p < .05$), while Marksmen showed higher levels of vocality ($b = 0.213$, $p < .05$), both when compared to the reference category of Tanks. These differences are shown in Figure 2. So, the Proteus effect does appear to occur, but it is not universal with every champion or champion type.

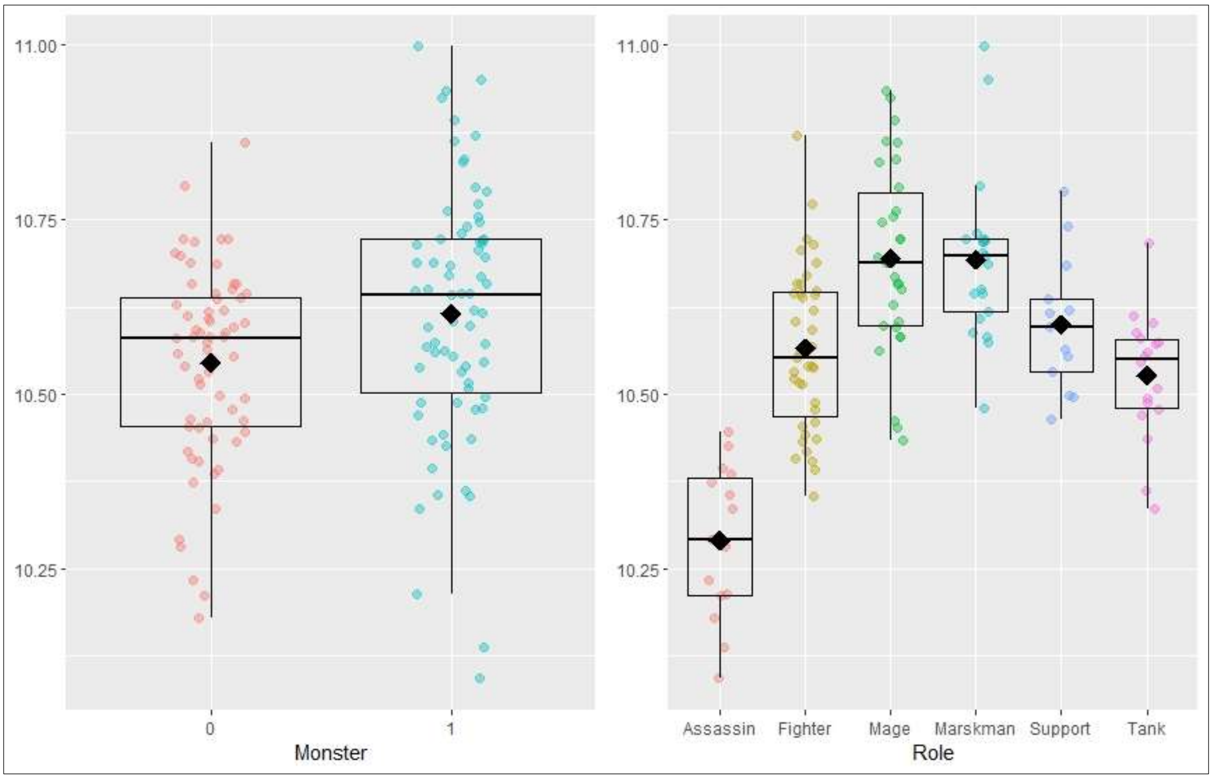

Figure 2: Comparison of the vocality model-predicted values for significant predictor variables. Diamonds indicate the mean; dots indicate actual data points. Boxplots are shown as an overlay.

4.3 RQ2: How Do Objective and Subjective Champion Attributes Affect a Player's Valence?

We proceeded by analyzing the model for valence, which is shown in Table 6.

Table 6: Hierarchical regression for valence, with unstandardized coefficients and standard errors. Significant results bolded.

Variable	**Model I**	**Model II**
Champion Body Type: Human	0.006 (0.003)	0.004 (0.003)
Champion Body Type: Monster	**0.011***** **(0.003)**	**0.009**** **(0.003)**
Champion Body Type: Animal	-0.001 (0.003)	-0.003 (0.003)
Champion Body Type: Mechanical	0.009 (0.005)	0.007 (0.005)
VBAS: Has weapon	-0.002 (0.003)	0.000 (0.003)
VBAS: Has smile	0.003 (0.003)	-0.001 (0.003)
VBAS: Shows teeth	-0.003 (0.003)	-0.006 (0.003)
Cultural Origin (Specific)	0.003 (0.003)	0.001 (0.003)
Cultural Origin (Fantasy)	0.001 (0.003)	0.003 (0.003)
Gender (Male)	-0.002 (0.002)	-0.001 (0.003)
Gender (Other)	0.007 (0.006)	0.010 (0.006)
Role (Assassin)	**-0.019***** **(0.005)**	**-0.021***** **(0.005)**
Role (Fighter)	-0.008* (0.004)	-0.009* (0.004)
Role (Mage)	**-0.015***** **(0.004)**	**-0.016***** **(0.004)**
Role (Marksman)	**-0.033***** **(0.004)**	**-0.038***** **(0.004)**
Role (Support)	-0.001 (0.005)	-0.004 (0.004)
Difficulty	-0.001 (0.002)	-0.002 (0.002)
Surprised		-0.005 (0.004)
Disgusted		0.002 (0.003)
Enjoying		0.001 (0.003)
Afraid		0.001 (0.005)
Sad		-0.008* (0.004)
Immersion		0.004 (0.005)
Attractiveness		0.001 (0.003)
Extrovert		0.000 (0.005)
Open		0.008 (0.005)

Variable	Model I	Model II
Conscientious		-0.007
		(0.004)
Agreeable		0.000
		(0.004)
Neurotic		0.004
		(0.003)
Dominance		**-0.015****
		(0.005)
Egoism		-0.004
		(0.005)
R^2	0.543	0.642
R^2 Δ	0.543	0.099*

Notes: *** p < 0.001; ** p < 0.01; * p < 0.05. The table shows the unstandardized coefficients, with standard errors in parenthesis.

As before, we begin by exploring the hierarchical nature of the model. The model containing only objective features explains 54.3% of the variance, whereas adding subjective features increases this by 9.9%, a significant change ($F(14, 104) = 2.048$, $p < .05$). This result indicates that for valence, subjective features also play a role, along with objective features.

Similar to what was found in toxicity, Monster champions exhibit some effects—notably, they have more positive valence than non-Monster champions ($b = 0.009$, $p < .01$). Roles, however, remain the most remarkable predictor. Assassins ($b = -0.021$, $p < .001$), Fighters ($b = -0.009$, $p < .01$), Mages ($b = -0.016$, $p < .001$), and Marksmen ($b = -0.038$, $p < .001$) all have more negative valence than the baseline category of Tank.

Regarding subjective features, two effects of note were found. First, the more a champion was perceived as sad, the lower was the degree of valence exhibited in the chat messages ($b = -0.008$, $p < .05$). An important thing to note, which is evident in the visualization, is the presence of an extreme outlier in the "Sad" measurement. This is the case for a specific champion—"Amumu, the Sad Mummy"—whose defining characteristic is being sad, with a corresponding depiction that deliberately emphasizes sadness. We kept the outlier since it is a legitimate one; regardless, for the sake of completion, we attempted to conduct the analysis without the outlier, and the results were consistent. Finally, higher levels of perceived dominance were also associated with more negative valence in the messages ($b = -0.015$, $p < .01$). A visualization for this model can be seen in Figure 3. So, again, the Proteus effect does appear to occur but not universally with every champion or champion type.

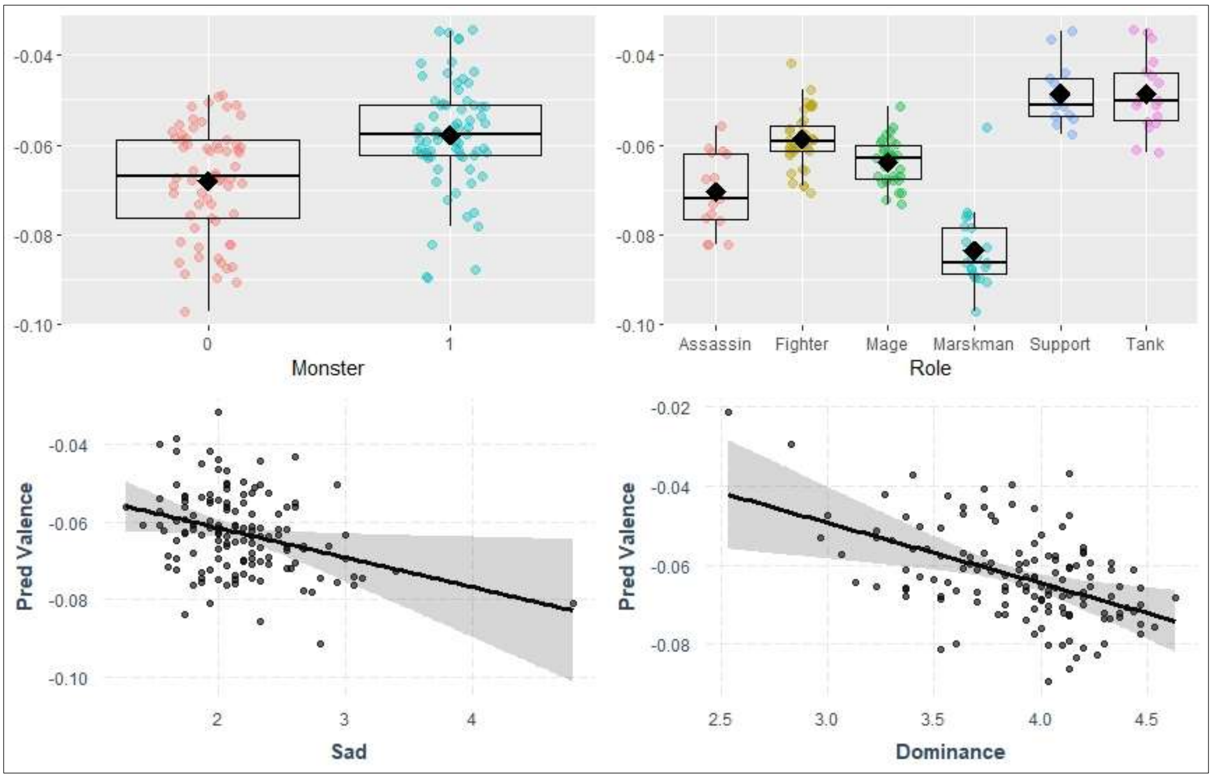

Figure 3: Upper half: Comparison of the valence model-predicted values for significant categorical predictor variables. Diamonds indicate the mean; dots indicate actual data points. Boxplots are shown as an overlay. Lower half: Partial regression plots for continuous variables. Shaded bands indicate 95% confidence intervals.

4.4 RQ3: How Do Objective and Subjective Champion Characteristics Affect a Player's Toxicity?

The model for toxicity is shown in Table 7.

Table 7: Hierarchical regression for toxicity, with unstandardized coefficients and standard errors. Significant results in bold.

Variable	Model I	Model II
Champion Body Type: Human	0.042 (0.044)	0.043 (0.047)
Champion Body Type: Monster	-0.043 (0.039)	**-0.095* (0.044)**
Champion Body Type: Animal	0.032 (0.043)	-0.002 (0.046)
Champion Body Type: Mechanical	**-0.203** (0.072)**	**-0.263*** (0.076)**
VBAS: Has weapon	0.033 (0.039)	0.052 (0.042)
VBAS: Has smile	-0.014 (0.033)	-0.028 (0.041)
VBAS: Shows teeth	-0.021 (0.034)	-0.019 (0.044)
Cultural Origin (Specific)	0.010 (0.041)	0.012 (0.044)
Cultural Origin (Fantasy)	-0.037 (0.042)	-0.035 (0.044)

Variable	Model I	Model II
Gender (Male)	**0.133*** (0.033)**	**0.132** (0.042)**
Gender (Other)	0.135 (0.083)	0.116 (0.091)
Role (Assassin)	**0.161** (0.060)**	**0.135* (0.065)**
Role (Fighter)	**0.225*** (0.049)**	**0.231*** (0.052)**
Role (Mage)	0.101* (0.051)	0.095 (0.054)
Role (Marksman)	**0.158** (0.055)**	**0.149* (0.059)**
Role (Support)	**-0.320*** (0.060)**	**-0.341*** (0.061)**
Difficulty	-0.007 (0.027)	-0.004 (0.030)
Surprised		0.054 (0.059)
Disgusted		0.007 (0.048)
Enjoying		0.034 (0.045)
Afraid		0.001 (0.065)
Sad		0.004 (0.049)
Immersion		-0.115 (0.064)
Attractiveness		0.009 (0.039)
Extrovert		-0.092 (0.067)
Open		-0.003 (0.074)
Conscientious		-0.014 (0.054)
Agreeable		0.036 (0.058)
Neurotic		-0.007 (0.046)
Dominance		-0.067 (0.071)
Egoism		0.006 (0.067)
R^2	0.600	0.647
R^2 Δ	0.600	0.047

Notes: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$. The table shows the unstandardized coefficients, with standard errors in parenthesis.

The first observation concerns the hierarchical nature of the model. Objective characteristics alone account for 60% of the model's explained variance, whereas introducing subjective features increases this amount by 4.7%, a change that is not significant ($F(14, 104) = 1.008$, $p = 0.451$). This suggests that objective characteristics, as a whole, are a more important predictor of toxicity. In fact, none of the subjective characteristics exhibited significant effects relating to toxicity.

With that said, several effects were noted for the objective characteristics. First, Mechanical champions exhibit lower levels of toxicity when compared to non-Mechanical champions ($b = -0.263$, $p < .001$). Similarly, but to a lesser degree, Monster champions also exhibit less toxicity ($b = -0.095$, $p < .05$). Also, when compared to female champions, male champions are associated with higher levels of toxicity ($b = 0.132$, $p < .01$).

Perhaps the most important aspect in predicting toxicity is the champion's role. When compared to the baseline category of Tank, Assassins ($b = 0.135$, $p < .05$), Fighters ($b = 0.231$, $p < .001$), and Marksmen ($b = 0.149$, $p < .05$) also exhibit higher levels of toxicity, whereas Support shows lower levels of toxicity ($b = -0.341$, $p < .001$). This effect can perhaps be attributed to the role each assigned class has in-game and how they interact both strategically and tactically with other players. Notably, the roles with higher levels of toxicity are those that have as their primary purpose attacking the enemy team, whereas roles that were more focused on team defense (i.e., Support and Tank) exhibit lower levels of toxicity. The results for this analysis are shown in Figure 4. Again, the Proteus effect does appear to occur limited to certain champions and champion types.

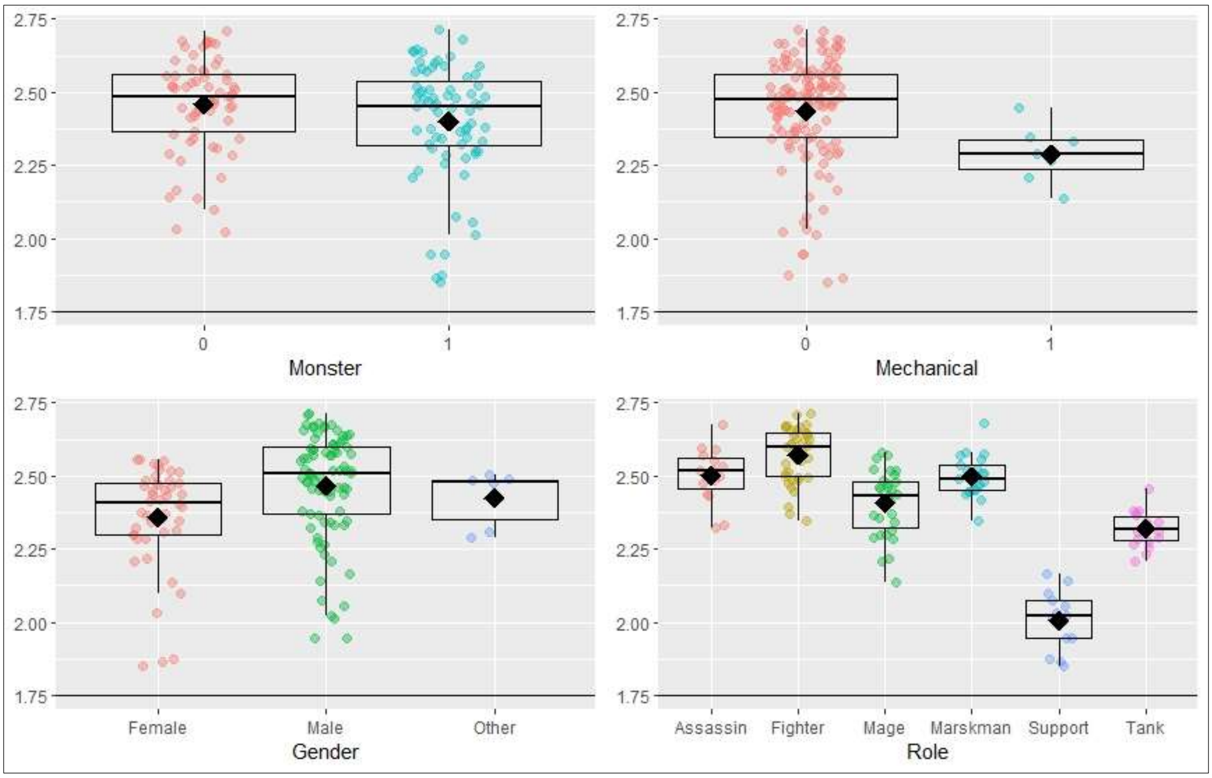

Figure 4: Comparison of the toxicity model-predicted values for significant predictor variables. Diamonds indicate the mean. Dots indicate actual data points. Boxplots are shown as an overlay.

4.5 RQ4: Do the Levels of Vocality, Valence, and Toxicity Change When a Player Changes Champions?

4.5.1 Procedure

To identify differences in the dependent variables when participants changed champions, a custom analysis was implemented in the following manner. First, for each champion played by a participant, we computed the absolute difference in DV scores for all combinations of games played with the same champion. Then we computed the average of absolute differences within champions ("Within Champions Average Delta" — henceforth, "Within Delta"). This serves as a measure of how much the DV changes, on average, when the participant is playing the same champion.

Then, we conducted the same calculation, but for games played with different champions. First, we calculated the average DV score for each champion played by the participant. Following this, for all combinations of champions played by the participant, we computed the absolute difference in average DV scores. Finally, we computed the average of absolute differences between champions ("Between

Champions Average Delta" — henceforth, "Between Delta"). This is a measure of how much a given DV changes on average as a participant shifts champions.

Following this, the Within and Between Deltas were compared with a paired-samples t-test (Hair et al., 2014). The rationale for this procedure is as such; if the Between Delta is significantly higher than the Within Delta, then it indicates that DV scores change significantly more when the participant plays different champions rather than when they play the same champion—in other words, the DV score is dependent on the champion played. Inversely, if the Within Delta is significantly higher, then the DV scores change more on a per-game basis than on a per-champion basis, indicating that the DV is more dependent on specific games than champions.

4.5.2 Results

The results for this comparison are shown in Table 8.

Table 8: Paired samples t-test for between and within average differences.

Variable	Between M (SD)	Within M (SD)	t (df)	P
Vocality	4.272 (2.193)	7.000 (2.511)	-55.296 (999)	<.001
Valence	0.554 (0.320)	0.369 (0.285)	15.410 (999)	<.001
Toxicity	3.269 (3.592)	3.064 (3.197)	4.439 (999)	<.001

First, vocality exhibits differences ($t(999) = -55.296$, $p < .001$) when contrasting Between and Within deltas, with the latter being significantly higher than the former. This indicates that variability is higher across games with the same champion, rather than across differing champions, suggesting that vocality varies on a per match basis, but not necessarily when the champion changes.

Second, valence also has significant differences ($t(999) = 15.410$, $p < .001$), but in the opposite direction, with between deltas being higher than within deltas, indicating that valence varies more across champions than it does across matches. As such, this suggests that valence is likely dependent on the champion being played.

Finally, toxicity has significant differences across between and within deltas ($t(999) = 4.439$, $p < .001$), with between deltas being significantly higher than within deltas. Similar to valence, this suggests that toxicity tends to vary more on a per champion basis. Figure 5 illustrates these comparisons. So, there does appear to be evidence of the Proteus effect for valence and toxicity but not vocality.

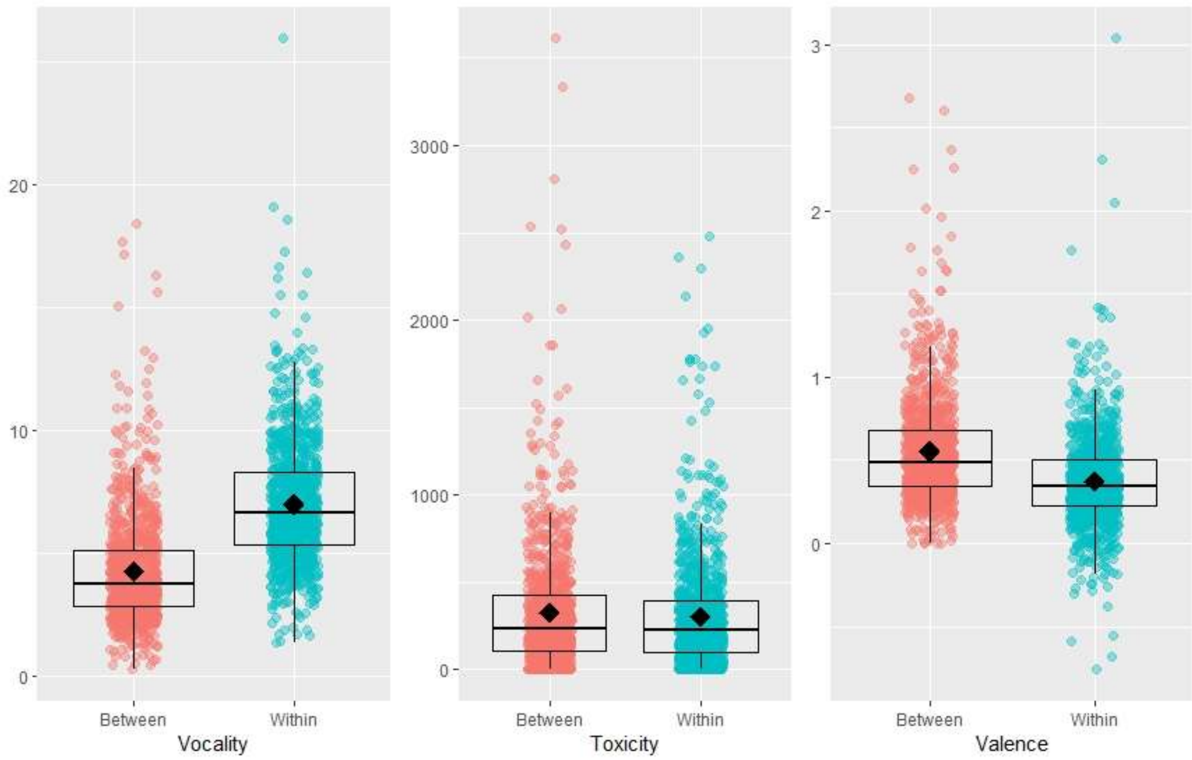

Figure 5: Comparison of mean between and within champion deltas for vocality, toxicity, and valence. Diamonds indicate the mean; dots indicate actual data points. Boxplots are shown as an overlay.

5 Discussion and Implications

In this study, we analyzed big chat data from one of the most popular competitive online games, League of Legends, to uncover whether the Proteus effect existed for LoL champions. We worked with two main sets of chat samples through separate methodologies. First, we sampled 13.6 million chat lines and investigated which characteristics of champions were better predictors of vocality, toxicity, and positive/negative valence in the communication of players who played those champions. Next, we sampled 1k, 2k, 3k, 4k, and 5k unique players who played multiple matches with different champions and investigated whether their vocality, toxicity, and valence in communication changed when they switched between champions. The findings of RQs are shown in Table 9.

Table 9: Findings for each Research Question (RQ) with Implication(s).

RQ	Key Findings	Implication(s)
Champion characteristics affect a player's vocality	• Few objective and no subjective characteristics had significant effects • Roles were the strongest predictor	Proteus effect is slight to non-existent as measured by players' vocality
Champion characteristics affect a player's valence	• Objective and subjective characteristics had significant effects • Roles were the strongest predictor	Proteus effect is present as measured by players' valence
Champion characteristics affect a player's toxicity	• Objective and subjective characteristics had significant effects • Roles and gender were the strongest predictors	Proteus effect is present as measured by players' toxicity
Change when a player changes between champions	• Vocality did not change much between champions • Valence did change between champions • Toxicity did change between champions	Proteus effect is present as measured by players' valence and toxicity

In general, our findings confirm the existence of the Proteus effect but not usually for all champions or champion types and, when comparing players between champions, for valence and toxicity but not for vocality. Our results confirm previous research wherein competitive offensive in-game roles raised toxicity and resulted in negative valence, while defensive roles did the opposite, providing insights into game design (Panourgias et al., 2014). A possible game design lesson from this outcome is that instead of being siloed into fixed offensive roles, game avatars and players can be rotated between offensive and defensive roles during gameplay to provide them with respite. If the champions can be designed in ways that with different skills sets they can alternate between roles, this would give the players an option of taking a step back from offensive and defensive roles between games. Moreover, game designers can mitigate the general toxicity of offensive characters by mobilizing design categories that increase valence. The combinations of gender, role, and body types with the most toxic potential can be used sparingly in character design. Interestingly, we found that the champion roles predicted and influenced toxicity and valence more strongly than the difficulty of play. The developers of online competitive games can benefit from focusing on player roles rather than difficulty levels to tackle toxicity in their games. Our results can indicate that difficulty options may not be the best way to combat toxicity in online games. Instead, character roles that carry higher stress or unbalanced distribution of group efforts are stronger sources of toxic communication.

One of our most interesting results was that the way a player communicated over in-game chat changed in valence and toxicity between champions—players can communicate and behave more positively or negatively in emotional terms and exhibit more toxic or less toxic behavior depending on the champion that they play as. However, the fact that this between-champion result was not observed for the vocality variable leads us to believe that while switching champions can affect the emotional mood of the player in communication, being vocal (choosing to communicate more or less) remains an issue that is tied to the person or context (e.g., how the success in the match is faring, etc.) with interesting implications for online gaming as learning (Xanthopoulou & Papagiannidis, 2012). This results leads us to believe that the players who stay less (or more) vocal, will do so independent of the champion that they play or the level of toxicity that their behavior have. On the one hand, players who are not very vocal will choose to stay silent even when they are feeling toxic; on the other hand, more vocal players are more likely to spread their mood whether be it positive or negative. Game developers can create systems in place to pinpoint vocal players and work with them toward improving the climate of the online gaming communities as they are the likely deployers of moods in games.

A second interesting result was the power of objective and coding-based characteristics predicting toxicity and vocality as compared to subjective characteristics. This leads us to assert that characteristics embedded in game content during the design processes are significantly more impactful on player behavior than perceptions regarding the champions. Previous research highlighted this relationship between game design features and the player-avatar relationship (Wang et al., 2019), as well as between game design features and loyalty (D. Choi & Kim, 2004), social behaviors (Türkay & Adinolf, 2019; Vegt et al., 2016), and other player behaviors in general (Apperley & Gandolfi, 2019). This is an interesting results because it highlights the responsibility of the game designers and the power of the work they do during the game creation process. A game community can work toward expanding on the perceptions of a game content through fan art, fan writing, etc., however, the values instilled in the game components during the initial design phase always stay as the strongest. On the other hand, valence was affected by both the objective and subjective characteristics, which was in line with our first finding in that how players perceived a champion's personality was indicative of how they would adjust their communication in-game. In short, players can express how they feel differently depending on the perceptions they project onto the champion they play, but the toxic behaviors emerge dominantly from champion's inherent design categories.

Third, it was surprising to see that champions that signified a monster type were less toxic, displayed more positive valence, and were highly vocal. The first two effects might feel counterintuitive to the Proteus effect; however, Švelch (2018) asserts that "*20th century popular culture, film and TV created an ever-expanding roster of monsters*" that was popularized and made accessible in the video game genre through franchises like *Pokémon*. It is concluded that video game monsters are less sublime and that "*rather than provoking awe and terror, they merely give players something to do*" (Švelch, 2018). Previous research also highlights that fighting with "*monster opponents makes game players feel less guilty and judge the player-controlled character as more morally justified*" (Lin, 2011). Our results hint at the possibility of a reverse effect, wherein controlling a monster character makes a player less toxic and emotionally more positive due to feeling less guilty about fighting with and virtually hurting other players. This explanation can also be valid for mechanical-type monsters (although few in number, see Table 2), wherein players have less negative feelings and guilt for fighting with other players and communicate in a less toxic way accordingly. More research is needed to expand on this result, but in general, speculative avatar design (one that is not based on common real-world human properties) can seemingly have stronger effects on the behaviors of users.

In contrast, it was less surprising to see offensive roles (assassins, marksmen, fighters, and mages) acting in a more toxic way and having less positive emotional valence, while the defensive roles (tanks and support) stayed as having lower toxicity and more positive emotional valence. Various previous studies (Anderson & Morrow, 1995; Schmierbach, 2010; Zhang et al., 2010) have highlighted the link between video game competition and aggressive behaviors during play. Offensive roles can be seen at the frontline of LoL matches and seemingly suffer from more stressful moments of conflict both inter- and intra-teams. Another result that can be discussed in the intersection with the champion roles was the champion difficulty (a rating created by the game developer). The champion difficulty was uncovered as not being impactful on toxicity, valence, or vocality. This is an interesting result because it shows that the effects of the difficulty of playing a champion is underwhelmed by the champion role. A champion with a challenging defensive role was still considerably less toxic than a champion with a very easy offensive role.

Finally, players playing with a male champion being more toxic was another interesting but perhaps unsurprising result. Previous research highlights the relationship between avatar gender, player gender, and in-game aggression. For example, Lehdonvirta et al. (2012) show how avatar gender can affect the in-game help-seeking behaviors of players regardless of players' real-world gender. Kaye et al. (2017) found that players with female avatars were perceived to be less competent in online games. Our findings, therefore, align with these previous studies in showing that the gender of the champion matters for the communicative style of players. These gender-based discrepancies highlight the need for the industry to continually and persistently address the inequalities regarding female avatars and players.

6 Limitations and Future Research

One limitation of the research was that the original data comes from a specific and limited number of IP-based geographies. This could have resulted in some cultural behaviors being presented as behavioral patterns for all players.

The second limitation was that our data only had text chat and did not contain any information about voice chat. We surmise that the data points that we looked at, such as vocality, toxicity, and valence, can change immensely between voice and text chat. However, we also propose that the text chat data was the better way to check the results of the Proteus effect since using one's own voice has the potential to break the immersion with the avatar and forefront's real-world identity rather than the avatar's.

The third limitation of our research was the lexicon we used to detect toxicity. Maher (2016) highlights that toxic players can bypass toxic language filters through unusual spelling and strategic use of spaces and other characters. Although our lexicon contains the most common unusual spellings of vulgar words, some toxicity might have remained undetected.

The final limitation of our data was champion skins. Each champion on LoL can have several skins, at the time of this study up to 17 skins, that change the way the champion looks. Usually, these changes are mostly based on garments and do not radically change who the avatar is; however, some skins can move champions between cultural domains and, as a result, have the potential to affect their priming, which in turn can affect the outcome of the Proteus effect. Our study does not account for the effects of different skins and only mobilizes default skin data. However, we did examine the number of skin changes, noting that more than 65% of the players relied on the default skin data, as shown in Table 10. So, we expect this limitation to have minimal impact on our findings, but it is an area for future research.

Table 10: Use of Skins by Champions.

Skins	% of Champions
Default	65.19%
1	5.28%
2	4.99%
3	4.66%
4	4.42%
5	4.75%
6 to 17	10.71%

Future research can address these limitations by replicating our methods for different gamer populations by mobilizing voice chat transcripts and reinforcing toxicity lexicons while factoring in the effects of different champion skins. Future research can also investigate cultural (Pronoza et al., 2021), and sexual harassment (Fox & Tang, 2017; W. Y. Tang et al., 2020) aspects of online gaming communication as additional manifestations of the Proteus effect in online communications and be a worthwhile extension of the research presented here. An additional area of research concerns the aspect of tilting (Sharma et al., 2021), which is an emotional state of frustration resulting in players becoming overly aggressive and adopting a less than optimal gaming strategy. The relationship between tilting and the Proteus effect would be an interesting line of research. This research would require the timing of game wins and losses, the communication among players at those times, along with the prior history of game outcomes by player. Although this is an exciting area for future research, our current dataset does not contain the necessary variables.

7 Conclusion

Video games are a medium that has a strong potential for social change when designed in prosocial ways (Fisher, 2020; Flanagan, 2006; Keating, 2016; Klimmt, 2009). Our study addresses two main issues around these discussions: (1) the *types of characters and roles that players can embody* in games (e.g., the Proteus effect, avatars, representations, cultural priming, etc.) and (2) the *game design decisions* that can mitigate or enhance toxicity and aggression. By being better informed about the effects of their design choices, game developers can move toward game and character designs that create more equitable and less toxic environments and online interactions.

Public policy makers and social policy institutions can fill in the research gap between the video games medium and its effects through proper funding and highlight the practical strategies that game developers as a private industry can adopt to create more prosocial products.

Overall, our results paint a picture wherein the game design process inherently affects how players behave in online interactions in those games. We assert this outcome after finding objective champion characteristics to be stronger predictors of toxicity and vocality. Although we find clear outcomes of the Proteus effect for these indicators, others had less power than we expected. As a result, we propose that game developers have a responsibility to understand and address the roots of players' communication behaviors—especially from the lens of character design.

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