Computers in Human Behavior 55 (2016) 605–613

Contents lists available at ScienceDirect

Computers in Human Behavior

journal homepage: www.elsevier.com/locate/comphumbeh

Full length article

What's in a name? Ages and names predict the valence of social interactions in a massive online game

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ARTICLE INFO

Article history:
Received 2 June 2015
Revised 20 September 2015
Accepted 22 September 2015
Available online 12 November 2015

Keywords:
Video games
Data mining
Age
Personality

ABSTRACT

Multi-player online battle arena games (MOBAs) are large virtual environments requiring complex problem-solving and social interaction. We asked whether these games generate psychologically interesting data about the players themselves. Specifically, we asked whether user names, which are chosen by players outside of the game itself, predicted in-game behaviour. To examine this, we analysed a large anonymized dataset from a popular MOBA ('League of Legends') – by some measures the most popular game in the world.

We find that user names contain two pieces of information that correlate with in-game social behaviour. Both player age (estimated from numerical sequences within name) and the presence of highly anti-social words are correlated with the valences of player/player interactions within the game.

Our findings suggest that players' real-world characteristics influence behaviour and interpersonal interactions within online games. Anonymized statistics derived from such games may therefore be a valuable tool for studying psychological traits across global populations.

1. Introduction

Online video games are played by hundreds of millions of people worldwide and fine-grained statistics on each game are constantly relayed to centralized servers where they can be stored and analysed. These games often require complex team strategies and permit direct personal interactions mediated by real-time chat, as well as inter-player rating mechanisms. They therefore represent a rich potential source of data for psychological investigation.

Previous research on relating personality traits to video game characteristics have often correlated findings from personality questionnaires with game data: either statistics collected within the game environment, or statistics about the amounts or types of games played (Chory & Goodboy, 2011; King, Delfabbro, & Griffiths, 2013; Park, Song, & Teng, 2011; Teng, 2008; Worth & Book, 2014; Yee, Ducheneaut, Nelson, & Likarish, 2011). This approach is valuable because personality questionnaires provide verified indicators about stable, real-life personality traits. However, respondents may respond untruthfully even to questionnaires administered anonymously across the internet and completing these questionnaires is time-consuming, thereby limiting the number of individuals who can be included in each study.

An alternative approach to the psychological analysis of gaming data is to 'mine' very large datasets for scientifically relevant relationships. This approach is interesting for several reasons. First, it is valuable to ask whether large datasets of this type are useful for statistical analysis at all. It may be, for example, that all players adopt a single 'optimal' strategy that leaves little room for personal variability, rendering these datasets uninteresting from a psychological viewpoint.

Secondly, if players do seem to exhibit systematic differences in behaviour, it might be that some of this variance is linked to real-world characteristics such as age, gender or personality (Worth & Book, 2014). Understanding these relationships could provide valuable information about these characteristics at a population level, and this information could be used as a preliminary screen to identify subjects who may be suitable for further testing. Finally, from a system design point of view, if reliable metrics on player behaviour can be established, they can be used to improve the social environment within the game.

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http://dx.doi.org/10.1016/j.chb.2015.09.034

1.1. Hypotheses

Here we examined correlations between the valence of in-game interactions and estimates of player age and anti-social tendencies in the massive online battle arena game 'League of Legends' (LoL). Here we define anti-social tendencies as being a propensity to engage in behaviour that breaches societal norms and which is likely to cause offense to a large proportion of people.

Because we are harvesting a large, anonymized dataset this study is correlational: We use two pieces of data extracted from usernames and use them to make estimates about the players real-world attributes. We then describe how these estimated variables correlate with in-game behaviour as assessed by the game-based reporting system. We discuss methodological issues relating to the accuracy of these inferences in detail at the end of the paper.

In LoL (Fig. 1) players join small, competing 'teams' that proceed to challenge each other for territory and an objective (overtaking the enemy base) in a relatively short time period (typically < 1 h). The precise details of the game are beyond the scope of this paper but there are abundant descriptions in online sources ("League of Legends," 2013). LoL is currently one of the most popular video games on the planet with an estimated 27 million online players every day (Gaudiosi, 2012). There are regular professional LoL tournaments with prizes worth millions of dollars and top players are eligible for US "internationally recognized athletes" visa status (Blake, 2013).

LoL players communicate through a real-time chat facility. This facilitates coordinated game play but it also allows players to interact socially. Players are also encouraged to evaluate their teammates at the end of each game. For example, players can praise each other for their teamwork or friendliness by sending 'Honor'. Alternatively they can submit 'Reports' chastising other players for deliberately playing badly or sending abusive messages through the chat system. This report system allows us to gather information about the average valence of each player's interpersonal interaction within the game environment. We hypothesized that if players' real-world personality types predict their behaviour within the game, the valence of these interactions might correlate with factors that are related to real-world behaviour. Two such factors are players' ages and their tendency to use foul or offensive language in their public usernames (DeWall, Buffardi, Bonser, & Keith Campbell, 2011; Holtzman, Vazire, & Mehl, 2010) – their 'anti-social naming tendency' (ANT).

We analysed players' self-chosen user names to estimate both age and ANT. Many of these user names contained information that informed us about these parameters. Specifically, players often embed their birth date in their user names (e.g. goodplayer1996) and in a separate analysis we show that these dates are highly-correlated with the self-reported ages of the players in the registration procedure. In addition, many usernames contain explicit or lightly obfuscated expletives, racial slurs and boasts that are clearly designed to attract attention (e.g.'g0ats3x'). Players must invest some time in generating these ANT names as multi-player online games typically have simple filters in place to block straightforward examples of offensive language.

Once we had identified user names that appeared to contain either age or ANT information, we asked if there was a relationship between ANT or age and the average valence of reports that each player sent or received within the game. We found that both age and ANT are predictive of in-game interaction valences as measured by honors and reports. Importantly, we find this effect for both incoming and outgoing ratings (in other words, ratings generated by a player and directed towards other teammates or, alternatively, ratings generated by teammates directed to a player).

2. Methods and materials

2.1. Data sources

Data were provided by the US-based company Riot Games (Santa Monica, CA)—the creators of League of Legends. To improve internet connectivity, Riot Games maintains servers around the world dedicated to particular geographic regions. The data described here were obtained from servers based in North America (NA), Western Europe (EUW), North Eastern Europe (EUNE), Turkey (TK), and Brazil (BR). Riot Games supplied a representative, random sample of 450,000 datasets—one for each player. This large dataset comprised of 100,000 players on each of the NA, EUW, EUNE and BR servers and 50,000 players from the TK servers. The data represent a snapshot of the accounts on the different servers on June 13, 2013. All accounts in the dataset had been created after November 1st, 2012. The number of datasets was chosen to be as large as possible while still remaining computationally tractable.

Our analysis of anti-social user names was based on data from just the NA server (allowing us to identify English language epithets). Our age analysis was based on all available datasets.

Strict controls were imposed of the type of data that were analysed. Data were collected and analysed in accordance with guidelines from both the Association of Internet Researchers (Markham & Buchanan, 2012) and the American Psychological Association (Kraut et al., 2004). It is important to note that only anonymized datasets were analysed. Researchers had no access to personal identifying information and no modification of players' online experience was performed as a result of this research. All players had agreed to Riot's Terms and Conditions as part of the LoL registration procedure and these explicitly allow LoL to use their data for

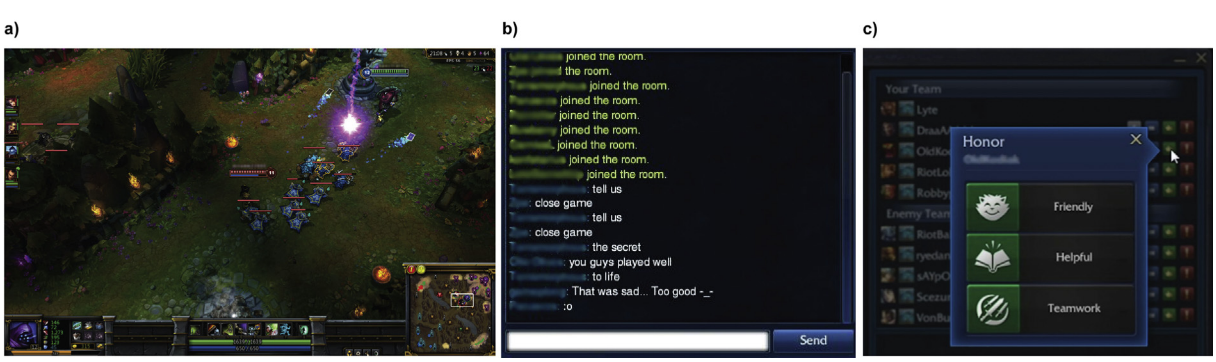

Fig. 1. Game play within League of Legends. a) A screenshot of a LoL match in progress. A small portion of the playing arena is shown (illustrated in the small inset box, bottom right). Individual player 'summoner names' or 'usernames' appear above the human-controlled characters along with a health indicator. b) In-game chat. Players are able to communicate with each other both during and after a game. c) Sending negative and positive reports is possible after each game ends. Here, a player is choosing to send a positive 'Honor' report about a teammate.

research purposes. All procedures described in this paper were approved by the University of York Department of Psychology ethical review board.

2.2. Interaction valence

After each League of Legends match, players are allowed to generate feedback on the behaviour of other team members via a point and click interface (Fig. 1c). Feedback can be positive ('honor') or negative ('reports') and can refer to a range of predefined behaviours (for example, 'Verbal abuse – Report', or 'Teamwork – Honor'). A single click on each of the feedback buttons generates a single instance of a report. Players can honor or report multiple team members at the end of each game but can only send a single feedback (either positive or negative) to each player. The accumulation of negative or positive reports can have consequences to a player. For example, large numbers of negative reports may lead to temporary or even permanent suspension of the player's account. Riot now implement a 'tribunal' procedure that allows other players to vote on these types of punishment and we note that the statistics of these tribunal events provide another rich dataset that may also relate to player personalities (Blackburn & Kwak, 2014). Although both positive and negative evaluations are nominally assigned to specific categories, in reality the nature of the infraction is sometimes unclear. For example, reporting a player for "intentional feeding" implies that they are deliberately playing poorly to benefit the opposing team but some aggressive players will use this accusation indiscriminately against anyone they consider to be inferior to themselves or to vent frustration when their team loses. There is also evidence that perceptions of toxic behaviour vary somewhat across cultures and geographic domains (Kwak, Blackburn, & Han, 2015).

Because we were interested in the overall valence of player behaviour, we used the mean of the combined 'report' and 'honour' metrics as scalar representations of negative and positive interaction. Outliers were removed using a robust outlier labelling heuristic (Banerjee & Iglewicz, 2007; Hoaglin, Iglewicz, & Tukey, 1986) which typically removed fewer than 1% of the data points. Report and Honor values were divided by the total number of games played and then log-scaled. Rates, rather than absolute levels were used to avoid conflating number of games played with average levels of anti-social or altruistic behaviour. The log transform was important to ensure that data distributions were approximately normal and therefore amenable to parametric statistical analysis. The resulting datasets were found to have equal variance as assessed by Levene's statistic.

Because the number of samples in each group was very high, these distributions were still found to be non-Gaussian by standard tests (Kolmogorov–Smirnov and Shapiro–Wilk tests; $p < .001$ in both cases) but inspection of Q–Q plots indicated relatively minor deviations. For the sake of completeness, we performed both parametric (ANOVA) and non-parametric (Kruskal–Wallis–with p-values indicated by 'KW') tests on our datasets and the results were found to be almost identical.

2.3. Antisocial names

A script containing a lexicon of common swearwords, slurs and sexual epithets as well as attention-drawing words and simple alphanumerical variations was created in MATLAB (Mathworks, MA). The list of words was derived initially from an online list (http://www.noswearing.com/dictionary). Additional common epithets and attention-seeking words were added by experienced game players and alphanumerical variation of the words (e.g. "g0ats3x") were also added algorithmically because players often use them to by-pass filters (Blashki & Nichol, 2005). Because we used databases of English language epithets, we restricted our search to data from the North-American Server (100,000 names). The full list of substrings used to identify antisocial names is provided in the supplementary material. This list of target words was not exhaustive but it nevertheless identified over 2000 antisocial names from the North American server. We asked whether mean Honor and Reports sent and received (four statistics in total) were different between players with ANT and the control group. To avoid issues of multiple comparisons resulting from performing four separate t-tests, we used a standard one-way ANOVA to evaluate the statistical significance of pairs of group differences. ANT data were compared to an equal-sized random sample of players with non-antisocial names extracted from the same server. Statistical analysis was performed in SPSS (SPSS IBM, New York, U.S.A) and Matlab (Mathworks, MA). Parametric means testing is generally robust to small deviations from normality when sample sizes are large and equal—as our datasets were (see above). Because significance depends on group size, we also include measure of the raw effect size in our analysis. The descriptive statistics for ANT vs non-ANT data are shown in Table 1.

2.4. Age

Age data were extracted from all servers. Years are conventionally indicated using either four (e.g. 1987) or two (87) digits. Consequently, an automated script identified dates within an appropriate 2- or 4-digit range (1985–2002) at either the beginning or end of the nickname ("1987Nickname", "Nickname87"). Because we were interested primarily in developmental changes up to adulthood, and because statistical tests on very small groups are unreliable, subjects over the age of 20 were not included in our analysis.

Clearly, not all instances of two or four digits matching a 'year' template actually indicate players' birth years. To examine this, we

Table 1
Descriptive statistics from ANT and random non-ANT players.

		N	Mean	Std. dev	Std. err	95% conf interval		Min	Max
						Lower	Upper		
Log(rep received)	ANT	2198	−1.707	.473	.010	−1.726	−1.687	−3.371	.572
	Random	2198	−1.838	.472	.010	−1.857	−1.818	−3.083	.166
Log(reports sent)	ANT	2198	−1.816	.537	.011	−1.838	−1.793	−3.373	.286
	Random	2198	−1.902	.555	.012	−1.925	−1.878	−3.729	.079
Log(honor received)	ANT	2198	−.973	.417	.009	−.990	−.955	−2.538	1.314
	Random	2198	−.910	.441	.009	−.929	−.892	−2.093	1.623
Log(honor sent)	ANT	2198	−1.314	.706	.015	−1.343	−1.284	−3.560	1.729
	Random	2198	−1.184	.752	.016	−1.216	−1.153	−3.604	1.975

Note. Values are log-scaled means of incoming and outgoing 'Reports' and 'Honor' feedback for each player.

obtained an additional dataset: the years of birth reported to Riot during the game registration procedure. These represent an independent, noisy estimate of player age. Ultimately, we obtained a total of 11,630 players who passed all the criteria with a mean age (estimated from the usernames) of 15.9 years. The distribution of birth years from all servers between the 1985 and 2002 (inclusive) are shown in Fig. 2a. We performed two separate analyses based on player ages. For the analysis in Fig. 2 (where we compare reported vs extracted dates of birth to assess the reliability of name-derived age estimates) we deliberately excluded ages less than 14 (year of birth 2000) from the final analysis. We did this to ensure that our results were unlikely to have been skewed by players lying about their age deliberately to pass the registration stage (Riot imposes a nominal minimum age of 13).

Age estimates from the two independent sources (usernames and registration) were correlated. Fig. 2b shows a joint histogram of 'name derived' vs 'reported' ages for a total of 10,299 players whose birth years lay between 1985 and 1999. The areas of the circles indicate the relative number of players that fall into each year.

Our data clearly show that many players use the same age in both their user names and during registration and we find a statistically significant correlation ($p < .001$) between the two measures with a medium to strong effect size (Pearson's $r = .53$, Spearman's $\rho = .51$). We note several interesting phenomena: The number '88' is an outlier in terms of its frequency of appearance in usernames. We believe this is likely due to its dual use as a cultural signifier (see Discussion). Players also tend to over-report the birth year 1990 during registration and there is a particularly strong correlation between players who report a birth year of 1990 and use the digits '2000' or '00' in their username. The reason for this is unclear but when this report year is omitted from the analysis the effect size for the correlation between reported and extracted date of birth increases to $r = .6$, $\rho = .58$ ('strong').

In the main analysis examining the relationship between age and interaction valence, we included the full set of 11,630 players with estimated ages as young as 11 (birth year 2002) because ages were estimated solely from username information which is not vetted. Players therefore have no reason to 'lie' about their date of birth in their usernames.

2.5. Analysis summary

- Players with antisocial usernames were identified using an enhanced dictionary lookup that accounted for alphanumeric substitutions in the NA dataset.
- Ages were estimated from the presence of two- and four-digit strings at the start or end of a name in all datasets. Cross-checking with registration data confirmed a high correlation between reported ages and the ages extracted from the user names.
- For all players, positive and negative interaction rates were computed from the means of the incoming and outgoing 'Report' and 'Honor' metrics. Rates were log-scaled to achieve near-normal distributions.

3. Results

3.1. Antisocial names

Out of the 3229 hits in the North American Server, 1031 nicknames were rejected as false positives after visual inspection by an expert English speaker who was blinded to the statistics associated with each name. For example, there would be nothing deliberately anti-social about the name "ThePen1sMightier" despite it generating a hit in the swear word dictionary lookup. After false positive

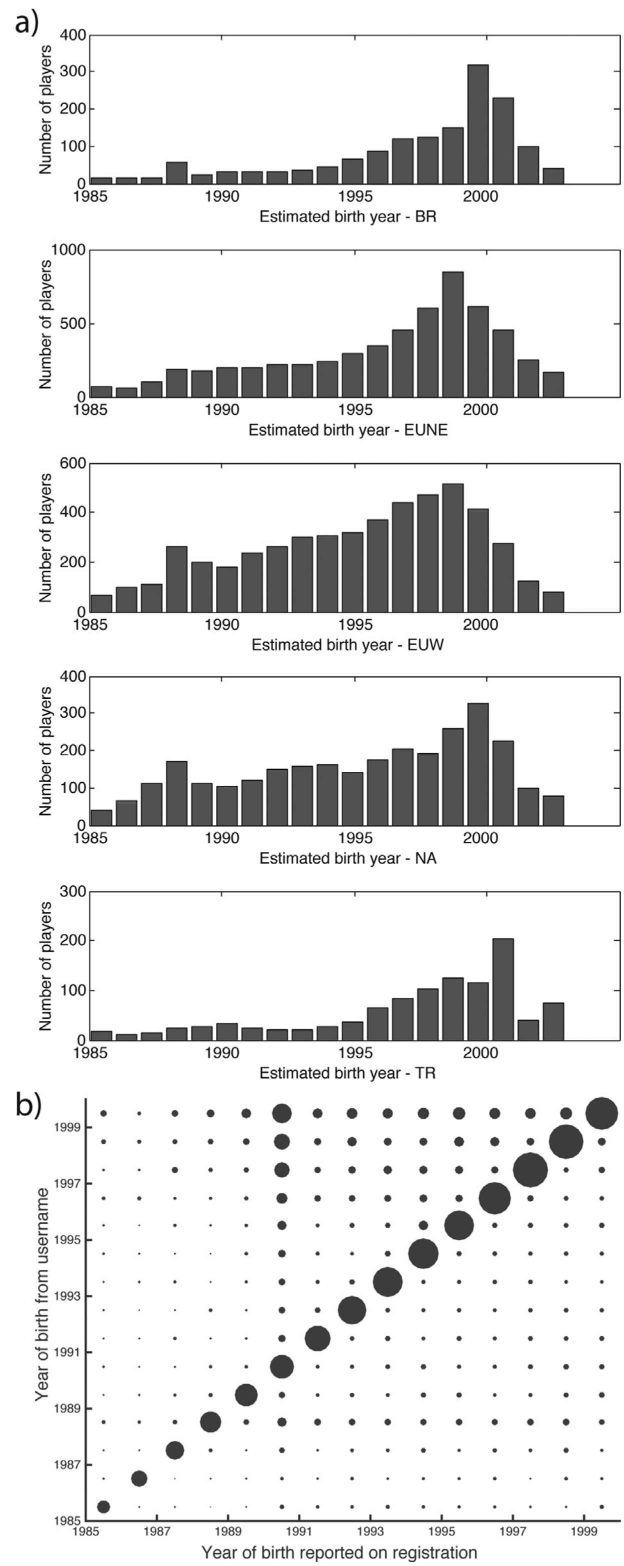

Fig. 2. a) Histograms of player ages estimated from usernames from five servers. Data are shown between estimated birth years 1985 and 2003 inclusive to illustrate the full shape of the distribution. b) Joint histogram of age estimates extracted from two different sources ($N = 10{,}299$) with birth years between 1985 and 1999. The area of each circle represents the number of players in each group. Age extracted from alphanumeric usernames correlates strongly (Pearson's $r = .60$) with age entered in the registration procedure.

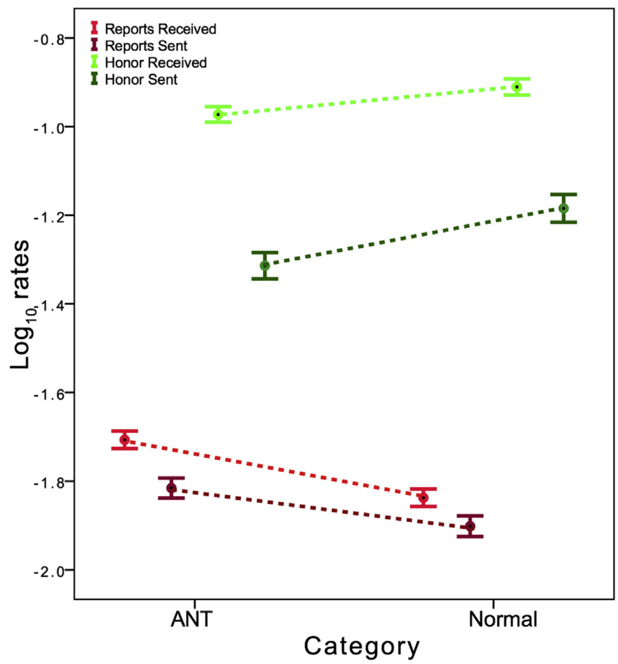

Fig. 3. There are significant differences between players with 'normal' and 'ANT' nicknames in all the traits we examined. Players with antisocial nicknames tend to have higher levels of negative incoming and outgoing interactions ('reports') and lower levels of positive interactions ('honor'). All differences are significant at $p < .001$. Error bars are ±1SEM.

rejection, we obtained a sample of 2198 users whose names were unequivocally designed to be anti-social – generally containing blatant racial, sexual or scatological epithets. An equal random sample of 'control' (non-antisocial) names from the North American server was selected for comparison so that the ANOVA was operating on groups of equal sizes. Human inspection of the control group identified no 'false negatives' or missed incidences of antisocial names.

We found that players with antisocial names had significantly higher *sent* ($F(1,4394) = 27.31$, $p < .001$, $\varepsilon^2 = .0064$, $r = .08$, *KW* $p < .001$) and *received* ($F(1,4394) = 84.2$, $p < .001$, $\varepsilon^2 = .02$, $r = .14$, *KW* $p < .001$) Report rates compared to the control group, reflecting an increase in anti-social behaviour. They also had significantly lower *sent* ($F(1,4394) = 34.517$, $p < .001$, $\varepsilon^2 = .0081$, $r = .09$, *KW* $p < .001$) and *received* ($F(1,4394) = 23.11$, $p < .001$, $\varepsilon^2 = .0049$, $r = .07$, *KW* $p < .001$) Honor rates, indicating a reduction in altruistic or prosocial behaviour. These differences are illustrated in Fig. 3.

Overall, our control group sent and received positive 'Honor' at a rate that was 25% higher than that of their antisocially-named peers. Similarly, antisocial-named players sent and received negative 'Reports' at a 25% higher rate than controls.

3.2. Age

We found a significant relationship between age and online interaction rates. First of all, we note that overall, all games generate around 8 times as many positive interactions as negative ones despite the fact that there are slightly more categories for negative compared to positive interactions. There was also no difference between the average number of games played at different ages.

However, we found that overall interaction rates (interactions per game) increase with age ($p < .001$) so that players at the highest end of the age range considered (27 years old) send, on average, 20% more interactions per game than those at the lowest end (11 years old). This overall increase in interaction is composed of opposing and statistically significant changes in the rates of the four interaction types: [positive (honor) or negative (reports)] × [incoming (initiated by other team members) or outgoing (initiated by the player themselves)].

The rate of all negative interactions decrease with age. Older players (22–26 years old) are significantly less likely to send or receive negative reports compared to younger players (11–15 years old). Conversely, the rate of positive interactions increases with age. These effects were highly significant ($p < .001$) in all cases (Fig. 4a).

As in the case of ANT data, the effect sizes of these age-related changes are small ($R^2 < .001$). As an example, the older players (22–26 years old) sent, on average, only 6% more positive interactions than younger players (11–15 years old). In comparison to the effect sizes seen in our analysis of username data, our ability to predict the behaviour of any individual player based on their estimated age is almost non-existent and the strong significance values we find are the result of having a large number of subjects. Our ability to predict changes in the *overall* behaviour of a particular age group is, however, excellent. A linear regression model fitted to the average ratio of positive to negative interactions (the 'valence' of overall interactions) gives an excellent fit ($R^2 = .8$, $p < .001$) – See Fig. 4b. On average therefore, player behaviour within LoL games experiences a slow, significant and linear increase between the ages of 11 and 26. This effect is seen equally strongly in the valence of both incoming and outgoing interactions.

4. Discussion

Although there is evidence from questionnaire-based studies that personality types are reflected to some extent in online game interactions (Worth & Book, 2014) and even in email addresses (Back, Schmukle, & Egloff, 2008), we ask here whether psychologically interesting information could be obtained purely from a large, anonymized gaming dataset. We chose to examine two game-independent attributes associated with individual players (age and antisocial tendencies) because information relating to both of these can be estimated from a single, publicly displayed data string chosen by the players themselves.

Naturally, these data are not perfect reflections of real-life player attributes. Numbers, for example, may reflect culturally significant digits rather than years. For example, '88' is a culturally laden number with Chinese speakers where it represents good luck. In addition, older players may attempt to appear younger to mislead other players with regard to their expertise and younger players may attempt to appear older to gain status. Nevertheless, our comparison of two independent estimates year of birth age (Fig. 2) suggests a strong correlation between ages extracted from usernames and those provided as part of the registration procedure.

It is possible that players choose user names that reflect a personality that they choose to adopt within the game rather than one that matches their own real-world personality. We find this plausible to some extent (video gamers are, after all, playful) but the extreme nature of some of the obscene usernames makes it unlikely that they are chosen by pro-social individuals even as a form of escapism. The age results are particularly encouraging in this respect as they correlate well with registration data and we believe that players are less likely to systematically choose alternative numerical data codes to propagate an alternative online personality although we are aware that certain numbers can be used to advertise an affiliation with extreme political beliefs (for example the number 88 also has significance within the culture of far-right Nazi sympathizers).

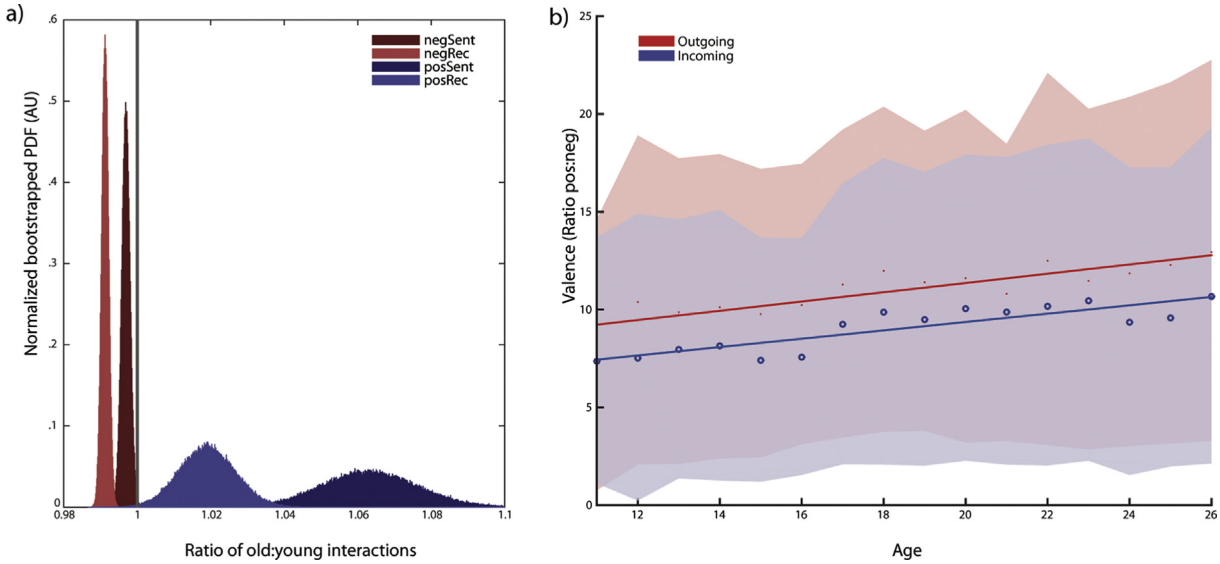

Fig. 4. The valence of interaction rates changes with age. a) Bootstrapped ratios of honor or report rates in older (22–26 year old) group compared to younger (11–15 year old) group as estimated from username data. Negative reports become less common (ratio old:young < 1) in the older group while positive 'honor' interactions become more common (ratio old:young > 1). On average, older players send approximately 6% more positive interactions and receive approximately 2% more positive interactions. b) The ratio of positive to negative interactions increases approximately linearly as a function of age.

4.1. Antisocial nicknames

Although the actual usernames cannot be reported here for reasons of privacy, they lie well outside the adult societal norms and there can be little doubt that they are specifically designed to shock or draw attention from other players. Although we have no other psychological information about the subjects who choose these names, it is plausible that they indicate real-life antisocial or attention-seeking tendencies and we are currently investigating this hypothesis in ongoing lab-based experiments.

We found a set of correlations that link these potential antisocial tendencies to the rate and valence of player–player interactions but correlation does not inform about causality. It is tempting to associate report and honor rates with performance and behaviour within the game (since this is the overt purpose of these metrics). By this account, antisocial naming tendencies are associated with antisocial game play leading to higher received report rates and lower received honor rates. But equally, it is possible that players with antisocial names receive negative reports solely because those names antagonize other players. In this context, we believe that the 'sent' metrics are particularly interesting because the ANT players themselves initiate these interactions. We found that players with ANT criticise their teammates more and praise them less than controls. In this case, the ANT names are unlikely to *cause* the negative valence of the interactions. Rather, both interaction metrics seem to reflect the underlying personalities of the players.

One intriguing possibility is that antisocial names are used to express affiliation to a particular group (or to differentiate players from their teammates). In this sense, the increased negativity associated with ANT players may be framed in terms of in-group and out-group behaviour with non-ANT players being more ready to punish and less ready to reward ANT players and *vice-versa*.

A final possibility is that the variables we examine are related through a third 'hidden' factor. For example, we considered the possibility that ANT players tend to perform worse than controls for other reasons and that their antisocial in-game behaviour was a result of this poor performance. Support for this hypothesis comes from recent studies showing that in-game antisocial behaviour is related to losing games (players who lose games are more likely to trade negative reports with their teammates) (Breuer, Scharkow, & Quandt, 2015). A full analysis of this type is beyond the scope of the current paper but we did examine this possibility in general by comparing the Match Making Rank (MMR) scores of ANT and control players: a proxy for player success. We found a very small, (but statistically significant: $p < .001$) *increase* in ANT MMRs compared to controls suggesting that increased failure levels per se were unlikely to account for the reduction in interaction valence that we measured for ANT players.

4.2. Age

We found significant changes in all our interaction metrics as a function of age. In summary, players become more pro-social as they age: negative interactions decrease and positive interactions increase. The effect is small at the individual level but extremely robust and significant at the group level. Adolescence is a period characterised by significant changes in important brain structures (amygdala, frontal lobes) that govern decision making (Galvan et al., 2006; Giedd et al., 1999). The faster maturation of the limbic system, when compared to that of the frontal lobe structures, may make adolescents more prone to react to emotionally salient situations/stimuli even when their logical reasoning is intact (Casey, Jones, & Hare, 2008; Gardner & Steinberg, 2005; Steinberg, 2004; Steinberg et al., 2009) thus driving the overall higher level of negative interactions in younger players.

Again, it is possible that the names (which embed the age data), rather than the behaviours are causal: older players may bully younger players during game play, thereby leading them to resort more to negative reporting as a retaliation strategy. Very young players may have played fewer games than older players and therefore be unaware of the societal norms within the game or become frustrated by playing against more expert opponents.

These factors are unlikely to explain the trends we observed. The data we examine here consist only of players with accounts opened in a relatively short time window between November 1st 2012 and June 13th 2013. All players therefore had approximately equal experience with the game and there was no effect of age on the number of games played. Very young players are in the minority – only 14% are less than 14 years old for example and the correlation between negativity and age is weak at the low age range, becoming stronger within the 14–27 age group. This supports the hypothesis that negative interaction rates reflect age-dependent cognitive changes in the players rather than a reaction to out-group discrimination based on their apparent age.

The increased ratio of negative to positive interactions in younger players may be due to the reduced cognitive control present in this age group. For example, (Dreyfuss et al., 2014) found increased sensitivity to threatening stimuli in adolescents, especially males which are the main demographic of LoL, even when they were instructed to ignore them. Thus it is possible that adolescents are unable to inhibit possible threatening stimuli leading to communicational escalations. The stimuli could relate to in-game events (for example getting killed), or to social interactions (for example, being criticised by another player).

The change in interaction valence could also be attributed to increases in Agreeableness/Benevolence with age; a trait related to cooperation as well as to the attribution of hostile intent to other agents' actions. Young people are more prone to misjudge a neutral message as a hostile one (Digman, 1997; Klimstra, Hale, Raaijmakers, Branje, & Meeus, 2009; Van den Akker, Deković, Asscher, & Prinzie, 2014) and a similar pattern has been observed in studies looking at both proactive and reactive aggression in young adolescents (Fite, Colder, Lochman, & Wells, 2008; van Bokhoven et al., 2006). Thus, in the context of a highly demanding competitive match, an otherwise neutral chat message could be misconstrued as offensive leading to increased reporting.

Age-dependent changes in interaction valence may also be driven by changes in cognition as well as personality (Blakemore, 2008). For example, according to (Dumontheil, Apperly, & Blakemore, 2010) adolescents commit more errors in a Theory of Mind task (ToM), when compared to adults while other studies have shown that tasks requiring ToM activate brain networks similar to those involved in empathy and forgiving (Farrow & Woodruff, 2005; Hayashi et al., 2010; Strang, Utikal, Fischbacher, Weber, & Falk, 2014). Dumontheil and colleagues (Dumontheil et al., 2010) concluded that the interaction between ToM and executive functions is still developing in late adolescence and we hypothesize that this is a factor in the slow increase in the valence of the interactions that we observe over age because younger players are unable to contextualize the actions of others correctly and may misattribute actions (such as accidental poor play) to a deliberate threat or collusion ('Intentional Feeding').

There is some anatomical basis for the changes in impulsivity and risk taking seen adolescence. A dominant theory is that the developmental trajectories of subcortical structures involved in reward (for example, the nucleus accumbens) are faster than those of more frontal cortical regions providing inhibition and cognitive control (Casey et al., 2008; Dreyfuss et al., 2014; Galvan et al., 2006). Again, this hypothesis predicts a slow but steady increase in pro-social behaviour and a decrease in impulsivity across the time frame covered by our data.

In the context of cognitive development, adolescent deficits in ToM might also be enhanced because they are deprived of valuable information such as facial and vocal cues which are an important source of information about other players' motives and emotions (Achim, Guitton, Jackson, Boutin, & Monetta, 2013).

Finally, an alternative possibility is that cognitive and behavioural difference are inherent to different birth cohorts rather than different ages per se. In other words, the increase in in-game antisocial behaviour that we observe in younger players will remain constant as those players become older: The millennials are simply more antisocial than those born before the turn of the century. Evidence for this hypothesis is mixed – largely because of the difficulty in performing well-controlled personality experiments spanning multiple generations. Recent work by Twenge et al. (Twenge & Foster, 2010; Twenge, Konrath, Foster, Campbell, & Bushman, 2008) suggests that millennials score higher on at least one antisocial personality trait (Narcissism) than age-matched cohorts from previous generations but this result has been disputed on methodological grounds and other researchers studying similar datasets indicate that any effect that may be present is very small and that a measure strongly related to narcissism ("self-enhancement") is stable across birth cohorts At the moment, therefore, we believe that the most parsimonious explanation for our data is based on a developmental change in personality across adolescence rather than a systematic difference in pre- and post-millennial birth cohorts.

4.3. Conclusions

Our data show that video games can provide a wealth of useful population-level information on developmental cognitive and psychological processes. Although the individual data points may be noisy, the overall conclusions are highly robust due to the sheer number of subjects. Similar analysis techniques have been used to examine the relationship between practise and performance in a custom-built online game as well as in MMORPGs (Stafford & Dewar, 2014) but we believe we are the first to examine player–player interactions in a MOBA game using this methodology (Drachen, Sifa, & Thurau, 2014; Guitton, 2010).

It is intriguing to ask if other clinical psychiatric disorders such as autism, sociopathy or addictive personality traits might be evident in these types of data. For example, since personality influences responses in experiments probing economic choice (Berg, Lilienfeld, & Waldman, 2013), can the same results be observed in video-games? Campbell and his colleagues supported the notion that in a classic "tragedy of the commons" game, where the individual needs to exert self-discipline and harvest a limited amount of the resources in order to allow for the continuous survival of all the players, the optimal strategy at a group level requires players to delay reward (Campbell, Bush, Brunell, & Shelton, 2005). Here, we expect players who have limited abilities to discount immediate gratification to have a stereotypical profile in complex online games such as LoL, which may alter long-term, in-game success rates both for themselves and for other team members. Conversely, it is also possible that positive in-game behaviour such as rapid learning, team building or leadership might correlate both with positive usernames and with positive personality traits in the real world.

Finally, we have assumed here that real-world personality attributes are the *cause* of the online behaviour patterns we observe. But it is possible that strategies learnt in the online environment may also provide cues to appropriate (or successful) behaviour in the real world.

Video game training alters a wide range of visual, cognitive and attentional mechanisms (Adachi & Willoughby, 2013; Appelbaum, Cain, Darling, & Mitroff, 2013; Boot, Kramer, Simons, Fabiani, & Gratton, 2008; Granic, Lobel, & Engels, 2014; Green & Bavelier, 2003; Li, Polat, Makous, & Bavelier, 2009) and regimes emphasizing different strategies within the same game can lead to changes in real-world behaviour (Greitemeyer & Osswald, 2010; Yoon & Vargas, 2014) and cortical activation patterns in subsequent test periods (Lee et al., 2012). It has been suggested that the remarkable plasticity evidenced in such studies is due in part to the highly arousing nature of the games themselves (Bavelier, Levi, Li, Dan, & Hensch, 2010). We are currently investigating the possibility that reinforcing altruistic strategies within a game environment condition players to modify antisocial behaviour in their day-to-day life.

Acknowledgements

We would like to thank Sam Ridgeway and Leonardo Galentsios for their valuable comments.

AVK supported by the IGGI doctoral training program provided by the EPSRC.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.chb.2015.09.034.

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