International Journal of Human–Computer Interaction

ISSN: 1044-7318 (Print) 1532-7590 (Online) Journal homepage: http://www.tandfonline.com/loi/hihc20

What Makes a Champion: The Behavioral and Neural Correlates of Expertise in Multiplayer Online Battle Arena Games

Yue Ding, Xin Hu, Jiawei Li, Jingbo Ye, Fei Wang & Dan Zhang

INTERNATIONAL JOURNAL OF HUMAN–COMPUTER INTERACTION
https://doi.org/10.1080/10447318.2018.1461761

What Makes a Champion: The Behavioral and Neural Correlates of Expertise in Multiplayer Online Battle Arena Games

Yue Ding[a], Xin Hu[b], Jiawei Li[b], Jingbo Ye[c,d], Fei Wang[a], and Dan Zhang[b]

[a]Department of Biomedical Engineering, Tsinghua University, Beijing, P.R. China; [b]Department of Psychology, Tsinghua University, Beijing, P.R. China; [c]Tobegin Inc, Chengdu, P.R. China; [d]Keahoral Inc, Shanghai, P.R. China

ABSTRACT

Despite the popularity of multiplayer online battle arena (MOBA) games, academic research on MOBA is still very limited. The current study aimed to fill this gap by exploring the behavioral and neural correlates of expertise for the most popular MOBA game, League of Legends (LOL). Three groups of LOL players with different expertise levels were recruited, including professional players, background-matched trainees, and age-matched students with no systematic LOL trainings. A series of behavioral tests and questionnaires was used to evaluate their general cognitive skills and their LOL-specific abilities were extracted from the neural activities (Electroencephalographs (EEG)s and Electrocardiographs (ECG)s) recorded during LOL matches. Using the behavioral features, both the students and the trainees could be significantly separated from the professional players (trainees vs. professional players, 61.11%; students vs. professional players, 66.67%), whereas the students and the trainees cannot be distinguished. Using the neural features, all three groups could be well separated with higher classification accuracies (students vs. trainees: 88.24%; trainees vs. professional players, 93.33%; students vs. professional players, 93.75%). The most contributing behavioral and neural indices were revealed as well, including multiple-object tracking capability, mental concentration, visuospatial attention ability, etc. The authors' results for the first time showed the possibility of recognizing MOBA expertise using both behavioral and neural measurements and provided a framework for evaluation, selection, and training of professional MOBA players.

1. Introduction

Multiplayer online battle arena (MOBA) is a game genre evolved from the real-time strategy genre in the early 2000s. In recent years, there has been a rapid growth of MOBA, making it one of the most popular game genres. The most popular MOBA game, i.e., League of Legends (LOL) developed by Riot Games, was reported to have over 100 million active players each month (Kollar, 2016). Despite such popularity and broad research interest, academic research on the expertise in MOBA is still in its infancy (Bonny, Castaneda, & Swanson, 2016; Ferrari, 2013).

As the most representative MOBA game, a typical LOL match usually lasts for about half an hour and involves two 5-player teams competing against each other on the game map. Each player controls a character ("champion") chosen from a roster of more than 100 champions, each of which has unique abilities and can be developed further during the match. Each team has a base ("nexus") located on the opposing corners of the map, protected by two layers of defensive structures ("towers"). The ultimate goal of the match is to destroy the opposing team's nexus. The early game usually focuses on gathering resources (by killing the enemy champions and AI-controlled minions and monsters) to develop one's own champion, while the late game focuses on attacking and defending of the towers and nexuses. Fights between opposing champions, both small-scale skirmishes as well as large-scale five-on-five team battles, occur frequently throughout the match, making it an intense experience to play the game.

With over 100 million monthly active players, MOBA's eSports scene is very active. In the case of LOL, there are many regional-level tournaments of various formats, such as leagues in which a number of professional clubs compete against each other on a regular basis, or cups in which teams try to eliminate others to reach the final round and win the championship. Annually, top teams from each region will compete in the World Championship Finals, which is equivalent to soccer's World Cup. LOL's 2016 World Championship Finals reached a peak concurrent viewership of 14.7 million (Bradmore & Magus, 2016). Researchers have employed LOL to study various aspects of MOBA, from the game design to social biology. For example, most MOBA games have a rank system, in which players climb the ranking ladder by winning matches; a study on LOL showed that the rank system shaped the ways players distinguished and narrated their game experiences, thus engendered a culture of collaboration and competition through distinction (Kou, Gui, & Kow, 2016). In the aspect of team performance, players' proficiency in played roles as well as team compositions predict better team performance, and expert players are better

CONTACT Dan Zhang dzhang@tsinghua.edu.cn Department of Psychology, School of Social Sciences, Tsinghua University, Beijing 100084, China; Fei Wang lukewang3126@gmail.com Department of Psychology, School of Social Sciences, Tsinghua University Beijing 100084, China.
Color versions of one or more of the figures in the article can be found online at www.tandfonline.com/hihc.

able to negotiate the dilemma between these two factors (Kim, Keegan, Park, & Oh, 2015). Furthermore, LOL is more than an online game; researchers have found similarities between LOL and online communities (Kwak, Blackburn, & Han, 2015). The teamwork during playing LOL could even help people develop a sense of belonging (Scholtes, Van Hout, & Van Koppen, 2016).

In contrast to such popularity and broad research interest in MOBA, the field of gaming expertise research is currently dominated by game genres such as puzzle games, action games, and first-person shooters. Compared to these types of games, MOBA is unique in that it requires a broader range of cognitive skills, from low-level ones such as hand-eye coordination to high-level ones such as strategical planning and team-working. Furthermore, the situation a player faces in a MOBA match is changing dynamically, which requires one to continuously monitor the battlefield and respond rapidly in the face of emergencies. This is mostly evident in the so-called ganking events, in which one or more players from one side try to organize a surprise attack on the players of the other side. A typical MOBA match is usually dotted with a lot of such events and successful dealings with them are crucial in winning the match. This complexity of gameplay poses significant challenges to MOBA players, yet the cognitive basis of expertise in MOBA is still poorly understood. In the following sections, we review the relevant literatures on expertise in video games and other sports.

1.1. The cognitive factors contributing to expertise in video games

A large and rapidly growing literature suggests that video game players (VGPs) perform better on many cognitive tasks than non-players (NVGPs) (Bisoglio, Michaels, Mervis, & Ashinoff, 2014; Green & Bavelier, 2015; Powers, Brooks, Aldrich, Palladino, & Alfieri, 2013). Visual attention, in particular, is one of the most important features involved in achieving a superior gaming performance. When performing a visual search task, VGPs showed faster response time compared to NVGPs, regardless of the difficulty levels (Castel, Pratt, & Drummond, 2005; Orozco, Self, Orozco, & Self, 2013; Wu, 2008; Wu & Spence, 2013). The findings suggest that relative to NVGPs, VGPs possess faster stimulus-response mappings in visual attention tasks. VGPs' advantages over NVGPs in other cognitive domains are more controversial. For example, it has been reported that VGPs were able to track two more objects than NVGPs in a multiple object tracking (MOT) task (Green & Bavelier, 2006), while other studies failed to find any meaningful difference between VGPs and NVGPs (Stothart, Boot, Simons, & Beyko, 2014). VGPs showed substantially superior eye–hand coordination than a matched sample of NVGPs, but no relationship was found between an individual's eye–hand coordination and the amount of time spent on video games (Griffith, Voloschin, Gibb, & Bailey, 1983). In virtual-reality-active video games, age influenced the eye–hand coordination strategies, as children had longer latencies and shorter fixation durations than adults (Chen & Tsai, 2015). Furthermore, some differences on cognitive performance seem to be restricted to specific game genres. For example, practice of competitive action video game could not improve the performance of Flanker test, but physics-based puzzle game could (Oei & Patterson, 2012).

The cognitive factors have also been explored by employing electrophysiological recordings to examine the modulatory effects of gaming experience and the dynamic changes during video gaming. Studies showed that the frontal midline theta-band activity increased over time during playing competitive sports game (He, Yuan, Yang, Sheikholeslami, & He, 2008), while the parietal–occipital alpha-band activity initially decreased, then increased slowly during gaming (Sheikholeslami et al., 2007). As frontal midline theta reflecting the mental concentration (Kubota et al., 2001), while the allocation of selective visuospatial attention relating to the alpha band over occipital regions of the cortex (Diepen, Miller, Mazaheri, & Geng, 2016; Foxe, Simpson, & Ahlfors, 1998; Śniady, Sieniawska, & Żukowski, 2014; Worden, Foxe, Wang, & Simpson, 2000), these results suggest that long, continuous play of video game might increase attention level of the players (Yamada, 1998). Emotion is another important factor that has been frequently studied in video gaming. For example, stronger asymmetry in frontal alpha activations toward the positive emotion direction was observed after game playing, together with increased empathy scores (Lianekhammy & Wilson, 2015).

Lastly, higher level dispositional variables, such as motivation, may also contribute to gaming expertise. For example, college students who frequently played video games were found to have a higher level of achievement motivation, being motivated to both master the game and compete with others (Morlock, Yando, & Nigolean, 1985).

Despite MOBA's popularity, only a few studies have examined the cognitive mechanisms of expertise in MOBA using behavioral tests, such as Flanker task, mental rotation, spatial span, etc. However, the results were either controversial or nonsignificant (Bonny et al., 2016; Ferrari, 2013).

1.2. The cognitive factors contributing to expertise in other sports

Given MOBA's competitive nature, studies on expertise in traditional competitive sports may also shed some light for studying MOBA expertise. One crucial ability for elite athletes is their ability to make superior anticipatory judgments as compared to less-skilled ones (David, 2015; Murray & Hunfalvay, 2016). This has been demonstrated in many different sports, such as badminton (Bruce Abernethy & Russell, 1987), gymnastic coaches (Moreno, Reina, Luis, & Sabido, 2002), soccer (Williams & Davids, 1998), and squash (Abernethy, 1990). The superior anticipatory ability is suggested to be related to their more efficient attentional allocation strategy and better visual search skills (Abernethy, 1990; David, 2015; Murray & Hunfalvay, 2016). Indeed, athletes have been shown to perform better on attention allocation in behavioral tests and have faster speed in visual processing than normal people (Mann, Williams, Ward, & Janelle, 2007; Voss, Kramer, Basak, Prakash, & Roberts, 2010). Training of visual attention using paradigms such as the 3D-

MOT has shown improvement for soccer players (Romeas, Guldner, & Faubert, 2016). Other high-level social psychological factors, such as Big Five personality dimensions, have also been shown to be associated with expertise in sport. For example, in Iranian national athletics, professional athletes' achievements were negatively correlated with neuroticism and positively correlated with extraversion, agreeableness, conscientiousness, and openness (Ghaderi & Ghaderi, 2012), and such effects might be mediated by self-determined motivation (Brinkman, Weinberg, & Ward, 2016).

The neural indicators for the expertise performance of elite athletes have mostly focused on bio-signals reflecting the activities of the autonomic nervous system (ANS), with relatively limited studies on those of the central nervous system (CNS). Heart rate (HR) and heart rate variability (HRV) are the most widely used neural indicators for ANS. Marathon runners' low-frequency oscillations of their HRVs at peak training load have been shown to be predictive of the athletic achievement (Manzi et al., 2009). Compared to non-elite athletes, elite speed skaters showed larger changes in HR and respiration and decreased motor neuron excitability, during mental simulation of voluntary motor actions. These inhibitory responses of the motor system may enhance actual motor performance under conditions of remarkably high mental stress, such as that which occurs in the Olympic games (Oishi & Maeshima, 2004). The characteristics of the CNS, however, are more complicated and less well studied. The massive body movement during sports imposes a major challenge for recording bio-signals from the CNS, such as the EEGs. Nevertheless, the existing studies focused on similar EEG components as for gaming expertise. For example, expert air-pistol shooters' occipital EEG alpha power was found to increase before the best shots, but to decrease before the worst shots (Loze, Collins, & Holmes, 2001). Frontal midline theta activity, an indicator of top-down selective attention, could also be used to distinguish an individual's best and worst golf putting performances during the pre-putt period (Kao, Huang, & Hung, 2013). Compared with expert golfers, novices performed with a relatively lower frontal midline theta due to their lack of experience and knowledge, which made them less able to focus on the demands of the specific task at hand (Kao et al., 2013).

1.3. Aims of the present study

To summarize, while extensive studies have been performed toward the understanding of expertise in both conventional sports and e-sports, the popular MOBA game has only been limitedly studied and is still poorly understood. The current study aimed to fill this gap by exploring the behavioral and neural correlates of LOL expertise, as LOL is the most popular MOBA game today. Three groups of LOL players with different expertise levels were recruited, and their behavioral performances of game-related cognitive functions as well as neural responses during LOL matches were collected. We applied univariate analysis (analysis of variance [ANOVA]), correlational analysis, and multivariate analyses (classification and regression) to identify major behavioral and neural factors contributing to the expertise in this most popular MOBA game.

2. Methods

2.1. Participants

Three groups of participants were recruited in the present study. Ten professional LOL players (all male, mean age 21 years, ranging from 18 to 24 years) from two Chinese LSPL (LOL secondary professional league) teams were the spotlight participants; seven of them were ethnically Chinese, and the rest three were ethnically Korean. Ten semi-professional LOL trainees (all male, mean age 18 years, ranging from 15 to 24 years) were recruited from a summer training camp held by Keahoral Inc., China, as the control group to match the professional background. These trainees were amateurs who have shown potentials in LOL and were being trained by professional coaches to improve their skills; the best among them might eventually become professional players. Another 20 undergraduate students (19 male, mean age 20 years, ranging from 19 to 21 years) from China Agriculture University, all of whom are casual-level LOL players and self-reported as playing the game frequently, were recruited as the control group to match the age of the professional players. The majority of them (14 out of 20) were qualified to play in the ranked league, which requires one to have played at least 300 matches. The age difference between trainees and professional players was significant (two-sample Wilcoxon rank sum test, $p = 0.03$), but there was no significance between students and professional players (two-sample Wilcoxon rank sum test, $p = 0.22$). Informed consent was obtained from all participants. The study was conducted in accordance with the Declaration of Helsinki and approved by the local Ethics Committee of Tsinghua University.

2.2. Procedure

The participants first completed six behavioral tests and two questionnaire scales, for an overall evaluation of their general gaming related cognitive and psychological abilities (see Figure 1). Then they were invited to play LOL online with both their EEGs and ECGs recorded, to assess their LOL-specific gaming abilities. The participants played one or two LOL games on the official game server in teams of five, i.e., two teams of professional players, two teams of trainees, and four teams of undergraduate students. Each player used his own LOL account, and each team was matched against an online team of a similar expertise level using LOL's official match-making system. The players were instructed to keep their verbal communication at a minimal level to reduce possible artifacts during physiological recordings. In total, 13 matches were completed, including 5 matches by the students, 4 matches by the trainees, and 4 matches by the professionals. The videos of all the games were recorded as well.

2.3. Tests for general abilities

Visual search, mouse tracking, Flanker test, and MOT were included in the present study, as they were reported to be representative of critical gaming-related abilities according to previous studies (see Section 1). Simple reaction time test was

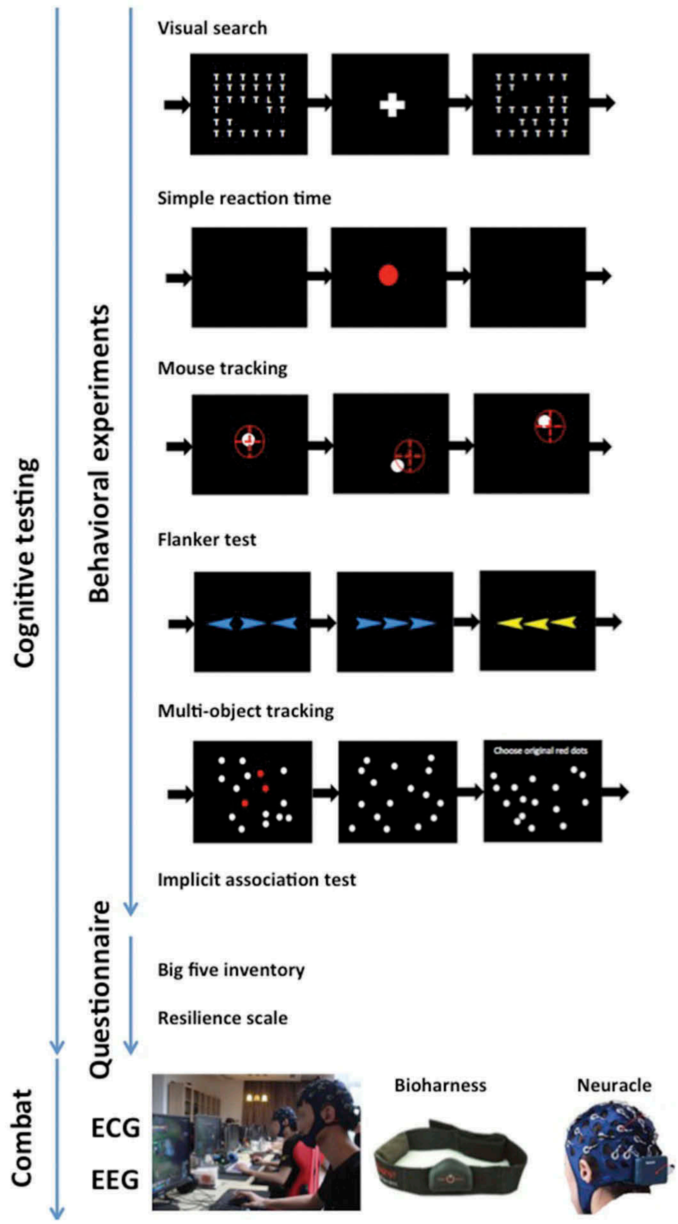

Figure 1. Experiment procedure.

also conducted to obtain the basic reaction time of three groups. The implicit association test (IAT) was employed to measure the participants' implicit level of achievement motivation (Brunstein & Schmitt, 2004). The paradigms were illustrated in Figure 1. The details of paradigm designs and the extraction methods of behavioral features were described in Appendix. Eight behavioral indices were extracted from the six tests, including accuracy changing rate from the visual search test (1), reaction time from the simple reaction time test (1), tracking precision and tracking stability from the mouse tracking test (2), response cost difference and task switching cost from the Flanker test (2), tracked dot number from the MOT test (1), and achievement intention score from the IAT test (1). Besides, the Big Five Inventory (BFI, John & Donahue, 1991) and the Resilience Scale (RS, Wagnild & Young, 1993) were administrated to quantify the participants' general personality and sociality. Specifically, the scores of agreeableness, conscientiousness, neuroticism, openness, and extraversion were calculated from BFI, while resilience was calculated from RS (refer to Appendix for the calculation details).

In total, eight behavioral indices and six questionnaire indices were obtained per participant, serving as the behavioral features for the following analyses. One undergraduate participant didn't finish the visual search test due to technical issues, and the three professional Korean players did not attend the IAT and the questionnaire scales, due to their insufficient Chinese language abilities.

All behavioral tests were programed in MATLAB (The Mathworks, USA) using the Psychophysics Toolbox 3.0 extensions (Brainard, 1997; Pelli, 1997). The questionnaire scale tests were implemented in an online survey platform (Sojump, China). The participants sat comfortably in a regular office environment and performed all tests on a computer, with a resolution of 1920 × 1080 ppi and a refresh rate of 60 Hz.

2.4. Tests for LOL-specific abilities

The participants were then invited to play one or two LOL matches while both ECG and EEG were continuously recorded. A chest-worn band (Bioharness 3, BioPac, USA) was used to record the ECG signals, and a 32-channel wireless EEG system (Neuracle, China) was used to record the brain activities (referenced at CPz and grounded at FPz). The sampling rates were 500 and 250 Hz for ECG and EEG recordings, respectively. The impedance was kept below 10 kOhm for all EEG recordings. Both recordings started at least 5 min before the beginning of the matches. A total number of 13 matches were recorded, among which the triggers of 1 match in the professional player group were lost due to equipment malfunction, leaving 12 matches' data for further analysis. The durations of the combats varied from 1251 to 3548 s, with an average of 1850 ± 652 s.

From the ECG and EEG recordings, critical ANS and CNS bio-signals were acquired. HR, HRV, and respiration rate (RR) were extracted from the ECG signals (Kim, Roberge, Powell, Shafer, & Williams, 2013). For EEGs, three indices were extracted: mental concentration, selective visuospatial attention, and emotion state. Specifically, the mental concentration was computed as the spectral power in the theta band (4–7 Hz) along midline frontal area (electrode Fp1); the selective visuospatial attention was indicated by the spectral power in the alpha band (8–12 Hz) over the occipital area (electrode O1, O2, Oz); the emotion state was reflected by the asymmetry of alpha power over the left and right frontal area (electrode F3 vs. F4), calculated as below:

$$alpha_{asym} = \ln\left(Power_{F4}^{alpha}\right) - ln\left(Power_{F3}^{alpha}\right)$$

Prior to these analyses, the recorded EEG signals were first band-pass filtered to 0.5–40 Hz and re-referenced to a common average reference. In addition, an independent component analysis was run to identify and reject the independent components that were possibly contaminated by artifacts (eye movement, muscle movement, etc.). The remaining ICs were then back-projected to the original EEG signal space for the artifact-free EEG signals. EEG data analyses were performed using Fieldtrip toolbox (Oostenveld, Fries, Maris, & Schoffelen, 2010) of MATLAB.

To explore the behavioral relevance of these bio-signals, the games were further coded based on the gaming videos, using two strategies. First, three 5-min data segments were extracted, i.e., the 5-min data right after the beginning phase of the games, the 5-min data in the middle phase of game playing, and the 5-min data before the ending phase of the games. Second, important gaming events were manually identified and extracted. Here, we focus on three types of major events: *laning*, *ganking*, and *battle*. Laning usually happens at the beginning of a match, in which two opposite players face each other on one of the three lanes on the map, trying to gather resources ("gold") by killing computer-controlled minions as well as harass the enemy from doing so, but without the intention of directly killing the opponent. Ganking refers the event in which one or more players from one side try to organize a surprise attack on players of the other side. Battle refers to other combat events that did not belong to ganking. These events were coded independently by two amateur LOL players (students from China Agriculture University). They first coded one match together to establish a common standard and then separately coded each of the rest matches. The coding results were compared and any inconsistency was solved by a third judge. A total number of 689 events were coded from the 12 games, including 307 lanings, 195 gankings, and 187 battles. The beginning time, ending time, and participating actors were logged for all the events. The abovementioned bio-signals were computed within these coded event and phase windows. For both event and phase windows, the 3 ECG features (HR, HRV, RR) and the 3 EEG features (frontal midline theta, frontal alpha asymmetry, occipital alpha) were calculated, resulting in 36 neural features in total (2 measurements × (3 events × 3 features + 3 phases × 3 features) = 36 features). These features were further corrected by dividing the corresponding data from the 5-min baseline before the beginning phase of the games.

The participants' expertise levels of LOL were evaluated by their tiers in the LOL ranked league system. The seven tiers (Bronze, Silver, Gold, Platinum, Diamond, Master, Challenger) were coded to 10–70. The 5 lower tiers were further divided into 5 divisions each, corresponding to 11–15, 21–25, and so on. Six participants in the student group were not included in further analysis because they had never played in the ranked league.

2.5. Data analysis

The analyses were first performed on each individual feature, including one-way ANOVA and correlational analysis. For ANOVA, the dependent variable was each feature, and the independent variable was the groups (student, trainee, and professional player). And then, the correlation coefficient was calculated between each feature and participants' ranks by Spearman's rank-order correlational analysis.

To take possible interactions among the features into consideration, multivariate analyses were then conducted. To test the predictability of the features for describing the professional player, Random Forest classifiers were constructed to perform binary classification between all the three possible pairs (students vs. trainees, trainees vs. professional players, students vs. professional players), based on all the features. The accuracies were obtained using leave-one-out cross-validation and then compared with a permutated chance level. The permutation test was run for 100 times, by shuffling the grouping labels of all individuals to acquire an estimation of the chance level. To further explore the contributing features for discriminating professional players from the others, a LASSO (least absolute shrinkage and selection operator) regression was employed, taking the ranks as the dependent variable and all the features as the independent variable. Behavioral features and neural features were first analyzed separately and then combined together. The features were normalized, and the ranks were centered, before performing the LASSO regression. By looping through all the possible desired numbers of nonzero features, the least number of features combined to reach significant regression was estimated, and meanwhile, the contributions of features were quantified by their beta parameters.

3. Results

3.1. Univariate and correlational analyses

Behavioral indicators

One-way ANOVA was conducted on each of the 14 features extracted from behavioral experiments to test the influence of participants' groups. Among them, significant main effect on the tracked object number ($F_{(2,30)} = 3.72$, $p = 0.04$) in MOT was observed (Figure 2(a)). The correlation coefficients between rank and each feature were calculated by Spearman's rank-order correlational analysis. The conscientiousness from BFI was significantly positively correlated ($r = 0.36$, $p = 0.04$, Figure 2(b)). Details of the statistical results can be found in Table A1 of Appendix.

Neural indicators

Similarly, the 36 features extracted from ECG and EEG were tested by one-way ANOVA and correlational analysis as well. Among the 18 ECG features, HRV during the middle and the ending phases as well as the ganking and the battle events were significantly influenced by the groups that the participants belonged to (Figure 3(a)). For EEG, all segments of midline theta, all events of alpha asymmetry, as well as occipital alpha during the ending phase and the ganking events, were significantly influenced by the groups (refer to Tables A2 and A3 in Appendix for the details of statistics). As revealed by Spearman's rank-order correlational analysis (Figure 3(b)), 14 neural features were significantly correlated with the ranks of participants. Among them, the two ECG features, HRV during the ending phase and the battle events, were positively correlated, while all the significant EEG features were negatively correlated to ranks (correlation coefficients shown in Figure 3(b), $ps < 0.05$). Notably, occipital alpha during all segments was significantly correlated with ranks. Frontal

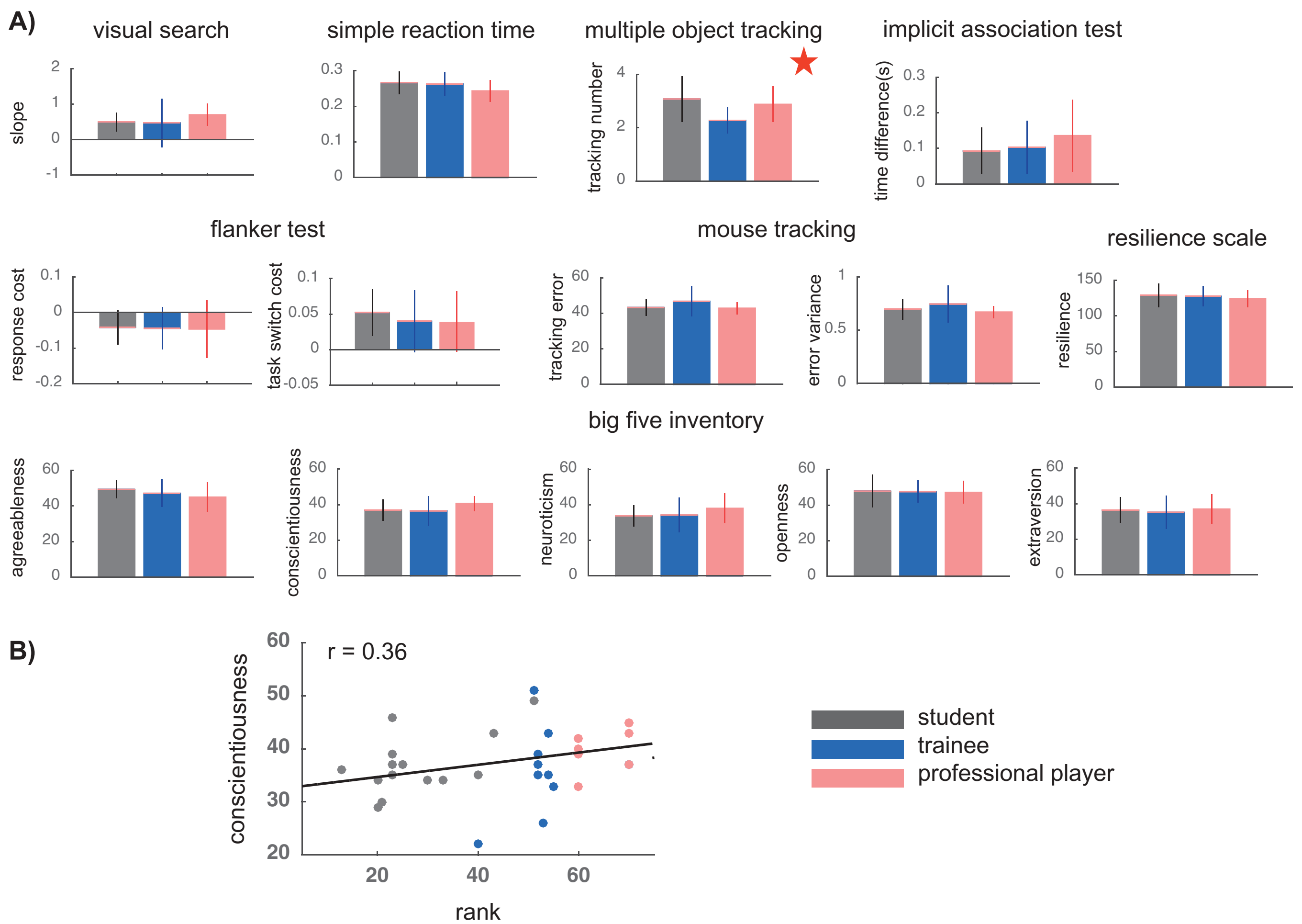

Figure 2. Univariate and correlational results of the behavioral features. (A) The average performance of the three groups in the behavioral tests and the questionnaires. Features marked by red stars were significantly influenced by the group factor ($p < 0.05$). (B) The features with significant correlation with participants' ranks ($p < 0.05$).

alpha asymmetry during the ganking events had the highest correlation coefficient ($r = -0.77$, $p < 0.01$).

3.2. Multivariate analyses

Multivariate analyses of classification and regression were then applied to the combination of the behavioral features, neural features, and all features to examine the prediction power of the features on either the participants' groups or ranks, as well as the major contributing indicators.

Classification

When using the behavioral features only, the student group couldn't be significantly separated from the trainee group (accuracy = 48.00%, permutation test, $p = 0.66$). In contrast, both the student and the trainee groups could be significantly separated from the professional player group (trainees vs. professional players, accuracy = 61.11%; students vs. professional players, accuracy = 66.67%; Figure 4). Using the neural features, all three groups could be well separated: students versus trainees: accuracy = 88.24%; trainees versus professional players, accuracy = 93.33%; students versus professional players, accuracy = 93.75%. When both features were combined together, all three groups can still be significantly separated, but the accuracies were not improved by adding behavioral features (students vs. trainees: accuracy = 64.71%; trainees vs. professional players, accuracy = 92.31%; students vs. professional players, accuracy = 92.86%).

LASSO regression

By manipulating the number of nonzero variables, LASSO regression using the 14 behavioral features showed a significant regression when using 2 nonzero features only ($R^2 = 0.14$, $p = 0.03$). The contributing features are the openness from BFI and the simple reaction time. When taking more features into the regression model, the remaining features entered the regression model in the order of conscientiousness, agreeableness, MOT track number, response cost difference from the Flanker test, neuroticism, achievement score from the IAT, task switch cost from the Flanker test, accuracy slope from the visual search test, precision from the mouse tracking test, stability from the mouse tracking test, resilience score, and extraversion from BFI (Figure 5(a)).

When applying LASSO regression using the 36 neural features, the most contributing feature was the frontal alpha asymmetry during the ganking events. Using only this specific

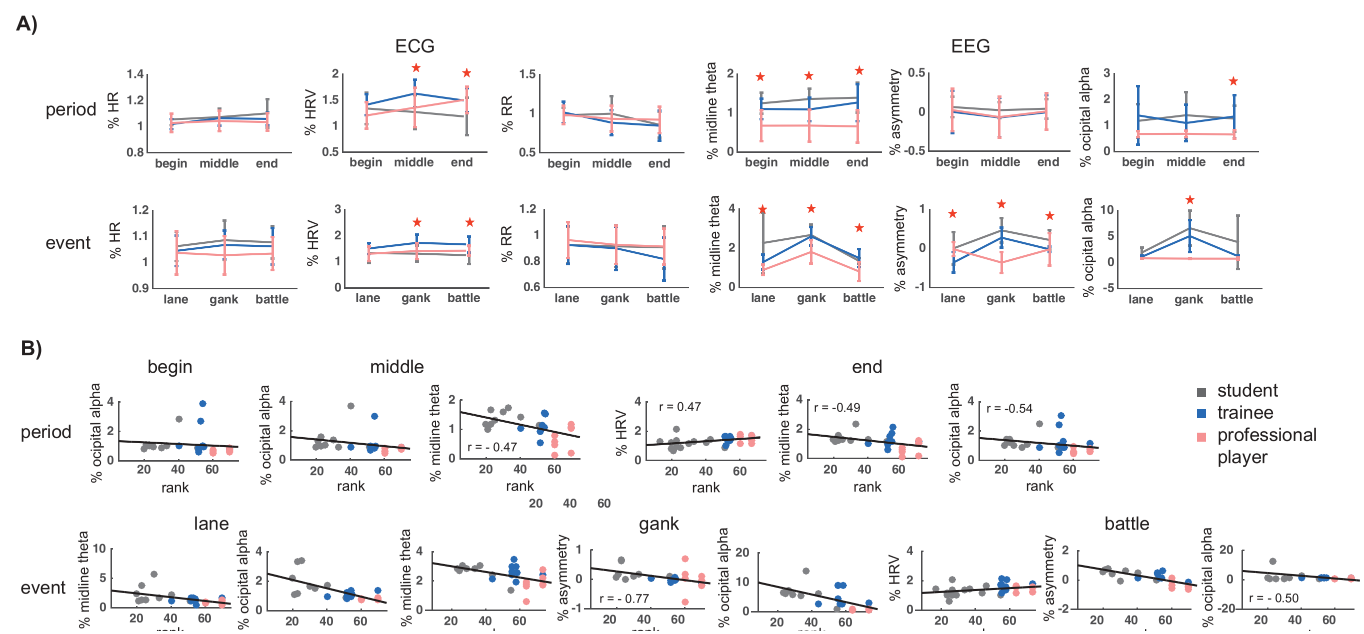

Figure 3. Univariate and correlational results of the neural features. (A) The average performance of the three groups measured by ECG and EEG. Features marked by red stars were significantly influenced by the group factor ($p < 0.05$). (B) The features with significant correlation with participants' ranks ($p < 0.05$).

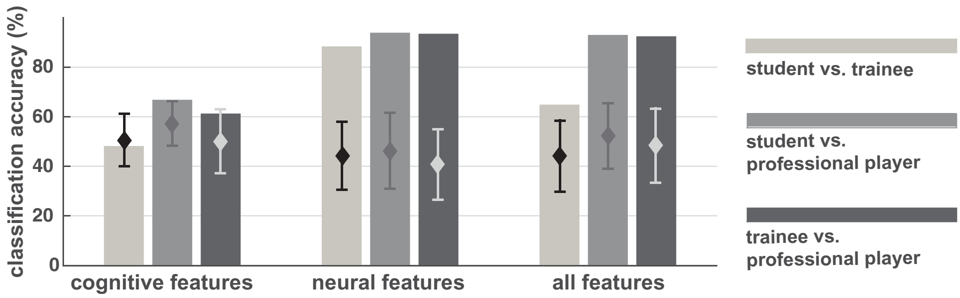

Figure 4. Classification results. Error bars indicate the accuracies from the permutation tests.

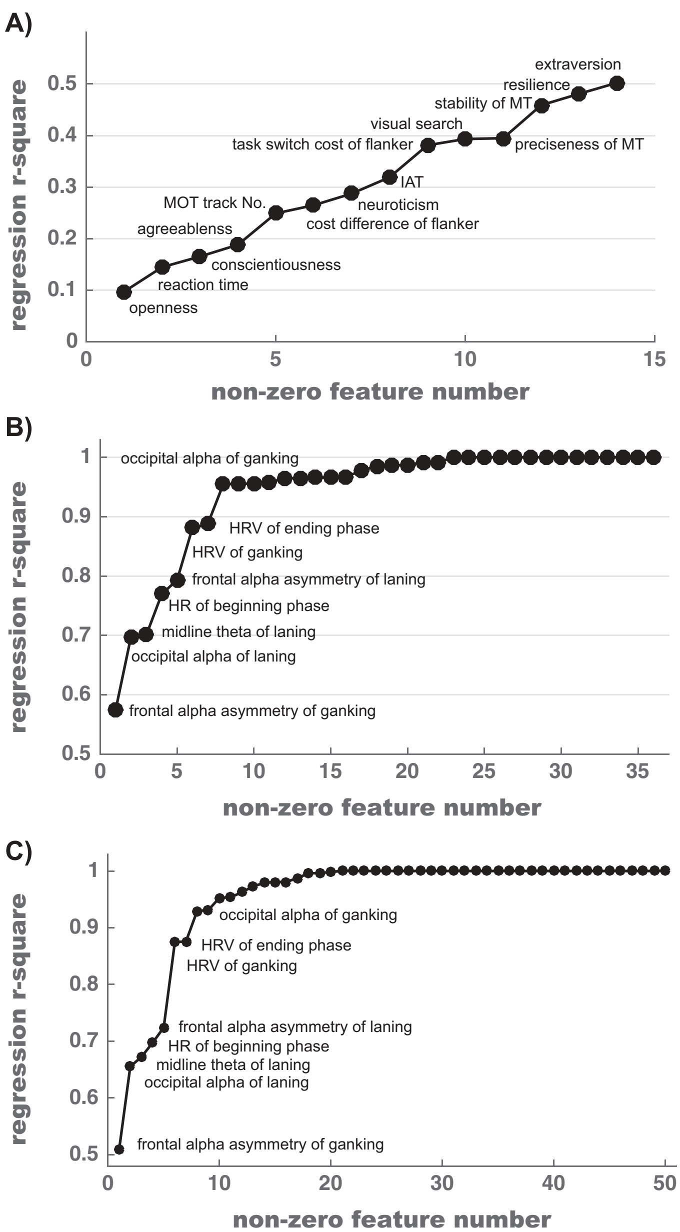

Figure 5. LASSO regression results. (A) Regression results using the behavioral features. (B) Regression results using the neural features. (C) Regression results using all features.

feature, the regression model is already significant (R^2 = 0.57, p < 0.01). The remaining features entered the regression model with increasing the number of nonzero features as follows: occipital alpha of the laning events, midline theta of the laning events, HR during the beginning phase, frontal alpha asymmetry of the laning events, HRV of the ganking events, HRV during the ending phase, and occipital alpha of the ganking events were left in order (Figure 5(b)).

Interestingly, when using all features, the first several major contributing features and their orders of entering the models were the same as using only neural features, although the regression accuracies were slightly influenced by the adding of behavioral features. Using only the frontal alpha asymmetry during the ganking events, the regression model was already significant (R^2 = 0.51, p < 0.01; Figure 5(c)).

4. Discussion

To reveal the key factors that may locate professional players or players with superior capacity to achieve success in MOBA games, as many as 14 behavioral features and 36 neural features were considered in the current study.

In the behavioral aspect, there were significant group differences on performances in the MOT paradigm. Such a finding is consistent with previous gaming expertise studies, suggesting that the ability to track multiple targets at the same time may provide critical edges for high-level players (Green & Bavelier, 2006; Romeas et al., 2016). During a LOL match, a player needs to divide his attentional resources onto multiple stimuli (e.g., teammates, enemy champions, the minimap, various feedback information, etc.) and continuously monitor them. Hereby, MOT ability is similarly important, if not more, for MOBA players. Besides, individual players' ranks in the LOL ranked league are positively correlated with their levels of conscientiousness. A higher level of consciousness indicates better self-control and a more careful style of behaviors (Mccrae & Costa, 1987), which may help a player to keep concentrated as well as to make fewer mistakes during a match.

In other cognitive tasks, the professional players did not show any superiority over the other groups, although previous studies have linked game experience with performances in some of the examined tasks, such as visual search (Castel et al., 2005; Orozco et al., 2013; Wu, 2008; Wu & Spence, 2013) or Flanker test (Oei & Patterson, 2012). This seemly inconsistency may be due to that previous results were based on game genres that required a different set of skills than MOBA. Compared to these genres, MOBA emphasizes less on a player's operational skill, but more on higher level capacities such as reading the circumstance, strategical planning, stress adaptability, and team cooperation.

Among the neural features examined, as many as 15 features showed significant group difference, while 14 features were significantly correlated with individual player's rank. In the ANS, HRV was a powerful measurement to tell the better players, especially during the ending phase of a match, in which both the professional and the trainee groups showed higher HRV than the students group. HRV usually decreases in the face of acute stressors (Karthikeyan, Murugappan, & Yaacob, 2013; Kaur, O'Kane, Moses, & Ikonomidou, 2014; Wang, Tanaka, & Chonan, 2008). Therefore, this result indicates that players with professional training are able to handle stress better during late-game when the gameplay becomes less structured and the situation becomes more unpredictable. In the CNS, midline theta activities distinguished professional players from the rest two groups through the whole match and all events. The other index of attention, occipital alpha activities, revealed similar pattern as midline theta during the three kinds of events. Furthermore, players with higher ranks had lower activities of occipital alpha throughout the matches. Both midline theta and occipital alpha have been established as indices of attentional level (Diepen et al., 2016; Kubota et al., 2001; Śniady et al., 2014); therefore, these results can be interpreted as the professional and higher level players were more concentrated over the whole course of a match. As a highly competitive game, MOBA requires high level of attention to follow the progress of the match as well as deal with emergencies such as sudden attacks all the time. Likewise, a similar front–parietal activation pattern has been reported in a previous game study, in which an immersive gameplay task was employed (Bavelier, Achtman, Mani & Föcker, 2012). Another significant index in the CNS was frontal alpha asymmetry during ganking and battle events, which was positive for the professional group, but negative for the trainees and the students group. Positive frontal alpha asymmetry value indicates stronger alpha activity in the right hemisphere than the left hemisphere, which has been reported to relate with negative emotion and stress response (Brouwer, Neerincx, Kallen, Leer, & Brinke, 2011; Gotlib, Ranganath, & Rosenfeld, 1998; Mikutta, Altorfer, Strik, & Koenig, 2012; Stewart, Coan, Towers, & Allen, 2014). Therefore, the result can be interpreted as the professional players were more relaxed and less stressful when fighting with the opponents. These neural findings are in line with one representative game study on MMORPGs (massively multiplayer online role playing games), which are similar to MOBA for their multitasking demands, strategical complexity, social interaction needs, etc. (Ang, Zaphiris and Mahmoud, 2007). In that study, the relationship between expertise and cognitive loads was studied, and the professional MMORPG players were suggested to have developed specific strategies to cope with the cognitive overloads. Our findings provide neural evidence for a less overloaded state of the professional MOBA players, possibly supporting and further expanding the cognitive overload theory for MMORPGs.

Notably, there were more significant neural features than behavioral features, and the neural features generally showed higher correlation coefficients with individual player's rank. These results suggested that MOBA involved mainly high-level cognitive functions, which were not captured in the cognitive tasks, but could be revealed in online measurements during a match. Moreover, such results call for the necessity of measuring neural activities during the behavioral tasks in future studies, which is expected to reveal more insights about the general cognitive abilities of MOBA expertise.

To build prediction models of the ranks or groups of the participants, multiple features were combined. In the classification between different groups, the combinations of the behavioral features could separate the professional players from the trainees as well as from the students, with better accuracy on the latter classification model. However, they were not as useful in separating the students from and the trainees. The employment of the neural features only, as well as the combination of all features, was able to separate the three groups from each other. Among these three kinds of combinations, the combination of the neural features had highest classification accuracies on all the three separations, suggesting that the behavioral features didn't provide additional information for classification. In the LASSO regression on individual player's rank, when using the combination of behavioral features, openness and simple reaction time were revealed as the most predictive factors. When combing neural features, all the three CNS features during laning made major contributions, together with frontal alpha asymmetry and occipital alpha activities during the ganking events. ANS provided the rest three major contributing features, HRV during the ganking evens and ending phase, as well as HR of the beginning phase. Compared with univariate results relying more on determined events and timing, the multivariate results showed that the performance difference was there from the very beginning. Adding the behavioral features to the neural features slightly influenced the prediction power, while the major contributing features remained the same as the combination of the neural features. Overall, these results suggest that a player's expertise in LOL could be readily predicted from behavioral and neural features, and online neural measures during the match provide the most predictive power.

The results of the present study have some practical implications. First, we have found that one's expertise in MOBA was associated with cognitive capacities such as MOT and personality traits such as consciousness. While these associations might be attributed to training effect, there is also some evidence suggesting that these characteristics are partially innate (Espeseth et al., 2012; Jang, Livesley, & Vernon, 1996). For professional MOBA eSports clubs, it might be fruitful to seek for new talent in individuals possessing such characteristics or develop training programs according to a trainee's individual weaknesses. Second, the online neural measures used in the present study, due to their close relations with overall MOBA expertise, can be used to develop a framework for evaluating a player's performance. Neural indicators such as occipital alpha activities and frontal alpha asymmetry can be continuously tracked throughout the match. If a player shows suboptimal level on one of the indicators (e.g., lack of concentration during certain period of the match indexed by high occipital alpha), specific training procedures could be employed to improve this aspect of the gaming performance. The effectiveness of a training procedure could also be evaluated through improvement on the indicator, even with real-time neural feedback. Such a framework would be useful in the training of professional MOBA players.

It should be noted that the present study has some limitations. First, although we were able to obtain data from a rare sample—professional MOBA players, the sample size is still quite small. Some of the nonsignificant results on the cognitive tasks might be partially due to low statistical powers. Future study may try to replicate the results of the present study and test their generalizability in a larger sample. Second, the data were cross sectional in nature, making it difficult to determine the direction of causality between cognitive capacities and training in MOBA. Future research employing a longitudinal design would be useful to differentiate the effects of innate capacities from training. Third, some of the measures we used were self-reported scales, which is vulnerable to biases such as social desirability. This could be an important shortcoming in certain application contexts such as selection of potential professional players. Future research could try to replace these explicit measures with implicit ones to tackle this issue.

Funding

This work is supported by National Key Research and Development Plan: [Grant Number 2016YFB1001200], National Social Science Foundation of China: [Grant Number 17ZDA323], MOE (Ministry of Education, China) Project of Humanities and Social Sciences: [Grant Number 17YJA190017] and Tsinghua University Initiative Scientific Research Program: [Grant Number 2014z21043].

References

Abernethy, B. (1990). Expertise, visual search, and information pick-up in squash. *Perception*, *19*(1), 63. doi:10.1068/p190063

Abernethy, B., & Russell, D. G. (1987). The relationship between expertise and visual search strategy in a racquet sport ☆. *Human Movement Science*, *6*(4), 283–319. doi:10.1016/0167-9457(87)90001-7

Ang, C. S., Zaphiris, P., & Mahmood, S. (2007). A model of cognitive loads in massively multiplayer online role playing games. *Interacting with Computers*, *19*(2), 167–179. doi:10.1016/j.intcom.2006.08.006

Bavelier, D., Achtman, R. L., Mani, M., & Föcker, J. (2012). Neural bases of selective attention in action video game players. *Vision Research*, *61*, 132–143. doi:10.1016/j.visres.2011.08.007

Bisoglio, J., Michaels, T. I., Mervis, J. E., & Ashinoff, B. K. (2014). Cognitive enhancement through action video game training: Great expectations require greater evidence. *Frontiers in Psychology*, *5*, 136. doi:10.3389/fpsyg.2014.00136

Bonny, J. W., Castaneda, L. M., & Swanson, T. (2016). Using an international gaming tournament to study individual differences in MOBA expertise and cognitive skills. *CHI Conference on Human Factors in Computing Systems ACM*, *2016*, 3473–3484.

Bradmore & Magus. (2016, December 7). 2016 league of legends world championship by the numbers. Retrieved from http://www.lolesports.com

Brainard, D. H. (1997). The psychophysics toolbox. *Spatial Vision*, *10*(4), 433–436. doi:10.1163/156856897X00357

Brinkman, C. S., Weinberg, R. S., & Ward, R. M. (2016). The big five personality model and self-determined motivation in sport. *International Journal of Sport Psychology*, *47*(5), 389–407.

Brouwer, A. M., Neerincx, M. A., Kallen, V. L., Leer, L. V. D., & Brinke, M. T. (2011). EEG alpha asymmetry, heart rate variability and cortisol in response to virtual reality induced stress. *Journal of Cybertherapy & Rehabilitation*, *4*(1), 83–99.

Brunstein, J. C., & Schmitt, C. H. (2004). Assessing individual differences in achievement motivation with the implicit association test. *Journal of Research in Personality*, *38*(6), 536–555. doi:10.1016/j.jrp.2004.01.003

Cain, M. S., Landau, A. N., & Shimamura, A. P. (2012). Action video game experience reduces the cost of switching tasks. *Attention, Perception, & Psychophysics*, *74*(4), 641–647. doi:10.3758/s13414-012-0284-1

Castel, A. D., Pratt, J., & Drummond, E. (2005). The effects of action video game experience on the time course of inhibition of return and the efficiency of visual search. *Acta Psychologica*, *119*(2), 217–230. doi:10.1016/j.actpsy.2005.02.004

Chen, Y., & Tsai, M. J. (2015). Eye-hand coordination strategies during active video game playing. *Computers in Human Behavior*, *51*(PA), 8–14. doi:10.1016/j.chb.2015.04.045

David, B. (2015). Anticipation and visual search in elite sport: the effects of anxiety, training and expertise (Unpublished doctoral thesis). Liverpool John Moores University, Liverpool, United Kingdom.

Diepen, R. M. V., Miller, L. M., Mazaheri, A., & Geng, J. J. (2016). The role of alpha activity in spatial and feature-based attention. *Eneuro*, *3*(5), 1–11. doi: 10.1523/ENEURO.0204-16.2016

Espeseth, T., Christoforou, A., Lundervold, A. J., Steen, V. M., Le, H. S., & Reinvang, I. (2012). Imaging and cognitive genetics: The Norwegian Cognitive NeuroGenetics sample. *Twin Research and Human Genetics*, *15*(3), 442–452. doi:10.1017/thg.2012.8

Ferrari, S. (2013). From generative to conventional play: Moba and league of legends. Paper presented at the Proceedings of DiGRA.

Foxe, J. J., Simpson, G. V., & Ahlfors, S. P. (1998). Parieto-occipital ~10Hz activity reflects anticipatory state of visual attention mechanisms. *Neuroreport*, *9*(17), 3929–3933. doi:10.1097/00001756-199812010-00030

Ghaderi, D., & Ghaderi, M. (2012). Survey the relationship between big five factor, happiness and sport achievement in Iranian athletes. *Annals of Biological Research*, *3*, 308–312.

Gotlib, I. H., Ranganath, C., & Rosenfeld, J. P. (1998). Frontal EEG alpha asymmetry, depression, and cognitive functioning. *Cognition and Emotion*, *12*(3), 449–478. doi:10.1080/026999398379673

Green, C. S., & Bavelier, D. (2006). Enumeration versus multiple object tracking: The case of action video game players. *Cognition*, *101*(1), 217–245. doi:10.1016/j.cognition.2005.10.004

Green, C. S., & Bavelier, D. (2015). Action video game training for cognitive enhancement. *Current Opinion in Behavioral Sciences*, *4*, 103–108. doi:10.1016/j.cobeha.2015.04.012

Griffith, J. L., Voloschin, P., Gibb, G. D., & Bailey, J. R. (1983). Differences in eye-hand motor coordination of video-game users and non-users. *Perceptual and Motor Skills*, *57*(1), 155. doi:10.2466/pms.1983.57.1.155

He, E. J., Yuan, H., Yang, L., Sheikholeslami, C., & He, B. (2008 May). EEG spatio-spectral mapping during video game play. International Conference on *Information Technology and Applications in Biomedicine*, 2008. ITAB 2008 (pp. 346–348), Shenzhen, China. Retrieved from http://ieeexplore.ieee.org/abstract/document/4570658/

Jang, K. L., Livesley, W. J., & Vernon, P. A. (1996). Heritability of the big five personality dimensions and their facets: A twin study. *Journal of Personality*, *64*(3), 577–592. doi:10.1111/j.1467-6494.1996.tb00522.x

John, O. P., & Donahue, E. M. (1991). The "Big Five" inventory: Versions 4a and 5b. *Notfallmedizin Up2date*, *18*(5), 367–385.

Kao, S. C., Huang, C. J., & Hung, T. M. (2013). Frontal midline theta is a specific indicator of optimal attentional engagement during skilled putting performance. *Journal of Sport & Exercise Psychology*, *35*(5), 470–478. doi:10.1123/jsep.35.5.470

Karthikeyan, P., Murugappan, M., & Yaacob, S. (2013). Detection of human stress using short-term ecg and hrv signals. *Journal of Mechanics in Medicine & Biology*, *13*(2), 1–29. doi:10.1142/S0219519413500383

Kaur, B., Durek, J. J., O'Kane, B. L., Tran, N., Moses, S., Luthra, M., & Ikonomidou, V. N. (2014). Heart rate variability (HRV): An indicator of stress. In *Independent Component Analyses, Compressive Sampling, Wavelets, Neural Net, Biosystems, and Nanoengineering XII, 9118*, 91180V. International Society for Optics and Photonics.

Kim, J., Keegan, B. C., Park, S., & Oh, A. (2015). The proficiency-congruency dilemma: virtual team design and performance in multi-player online games. *CHI Conference on Human Factors in Computing Systems*, 4351–4365.

Kim, J. H., Roberge, R., Powell, J. B., Shafer, A. B., & Williams, W. J. (2013). Measurement accuracy of heart rate and respiratory rate during graded exercise and sustained exercise in the heat using the Zephyr BioHarness™. *International Journal of Sports Medicine*, *34*(6), 497.

Kollar, P. (2016, September 13). The past, present and future of league of legends studio riot games. Retrieved from http://www.polygon.com

Kou, Y., Gui, X., & Kow, Y. M. (2016). Ranking practices and distinction in league of legends. *Symposium on Computer-Human Interaction in Play*, 4–9.

Kubota, Y., Sato, W., Toichi, M., Murai, T., Okada, T., Hayashi, A., & Sengoku, A. (2001). Frontal midline theta rhythm is correlated with cardiac autonomic activities during the performance of an attention demanding meditation procedure. *Cognitive Brain Research*, *11*(2), 281–287. doi:10.1016/S0926-6410(00)00086-0

Kwak, H., Blackburn, J., & Han, S. (2015). Exploring cyberbullying and other toxic behavior in team competition online games. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems*, 3739–3748.

Lianekhammy, J., & Wilson, R. W. (2015). Links to prosocial factors and alpha asymmetry in adolescents during violent and non-violent video game play. *Child Studies in Asia-Pacific Contexts*, *5*(2), 63–81. doi:10.5723/csac.2015.5.2.063

Loze, G. M., Collins, D., & Holmes, P. S. (2001). Pre-shot EEG alpha-power reactivity during expert air-pistol shooting: A comparison of best and worst shots. *Journal of Sports Sciences*, *19*(9), 727. doi:10.1080/02640410152475856

Mann, D. T., Williams, A. M., Ward, P., & Janelle, C. M. (2007). Perceptual-cognitive expertise in sport: A meta-analysis. *Journal of Sport & Exercise Psychology*, *29*(4), 457. doi:10.1123/jsep.29.4.457

Manzi, V., Castagna, C., Padua, E., Lombardo, M., D'Ottavio, S., Massaro, M., … Iellamo, F. (2009). Dose-response relationship of autonomic nervous system responses to individualized training impulse in marathon runners. *Ajp Heart & Circulatory Physiology*, *296*(6), 1733–1740. doi:10.1152/ajpheart.00054.2009

Mccrae, R. R., & Costa, P. T. (1987). Validation of the five-factor model of personality across instruments and observers. *Journal of Personality & Social Psychology*, *52*(1), 81–90. doi:10.1037/0022-3514.52.1.81

Mikutta, C., Altorfer, A., Strik, W., & Koenig, T. (2012). Emotions, arousal, and frontal alpha rhythm asymmetry during Beethoven's 5th symphony. *Brain Topography*, *25*(4), 423. doi:10.1007/s10548-012-0227-0

Moreno, F. J., Reina, R., Luis, V., & Sabido, R. (2002). Visual search strategies in experienced and inexperienced gymnastic coaches. *Perceptual and Motor Skills*, *95*(3), 901–902. doi:10.2466/pms.2002.95.3.901

Morlock, H., Yando, T., & Nigolean, K. (1985). Motivation of video game players. *Psychological Reports*, *57*(1), 247–250. doi:10.2466/pr0.1985.57.1.247

Murray, N. P., & Hunfalvay, M. (2016). A comparison of visual search strategies of elite and non-elite tennis players through cluster analysis. *Journal of Sports Sciences*, *35*(3), 241–246.

Oei, A., & Patterson, M. (2012). Video game training improves visual cognition: A multiple game study. *Journal of Vision*, *12*(9), 689. doi:10.1167/12.9.689

Oishi, K., & Maeshima, T. (2004). Autonomic nervous system activities during motor imagery in elite athletes. *Journal of Clinical Neurophysiology*, *21*(3), 170–179. doi:10.1097/00004691-200405000-00005

Oksama, L., & Hyönä, J. (2008). Dynamic binding of identity and location information: A serial model of multiple identity tracking. *Cognitive Psychology*, *56*(4), 237. doi:10.1016/j.cogpsych.2007.03.001

Oostenveld, R., Fries, P., Maris, E., & Schoffelen, J. M. (2010). FieldTrip: Open source software for advanced analysis of MEG, EEG, and invasive electrophysiological data. *Computational Intelligence & Neuroscience*, *2011*(3), 156869.

Orozco, J., Self, E., Orozco, J., & Self, E. (2013). Action video game players can perform visual search faster, but show the same attentional capture. *Journal of Vision*, (9). doi:10.1167/13.9.163

Pelli, D. G. (1997). The VideoToolbox software for visual psychophysics: Transforming numbers into movies. *Spatial Vision*, *10*(4), 437. doi:10.1163/156856897X00366

Powers, K. L., Brooks, P. J., Aldrich, N. J., Palladino, M. A., & Alfieri, L. (2013). Effects of video-game play on information processing: A meta-analytic investigation. *Psychonomic Bulletin & Review*, *20*(6), 1055–1079. doi:10.3758/s13423-013-0418-z

Romeas, T., Guldner, A., & Faubert, J. (2016). 3D-multiple object tracking training task improves passing decision-making accuracy in soccer players. *Psychology of Sport & Exercise*, *22*, 1–9. doi:10.1016/j.psychsport.2015.06.002

Scholtes, V., Van Hout, M., & Van Koppen, L. (2016). Can people develop a sense of belonging throughplaying league of legends? *International Conference on Advances in Computer Entertainment Technology*, 11.

Sheikholeslami, C., Yuan, H., He, E. J., Bai, X., Yang, L., & He, B. (2007). A high resolution EEG study of dynamic brain activity during video game play. *International Conference of the IEEE, the Engineering in Medicine and Biology Society*, 2489.

Śniady, P., Sieniawska, R., & Żukowski, S. (2014). Occipital Alpha Activity during Stimulus Processing Gates the Information Flow to Object-Selective Cortex. *Plos Biology*, *12*(10), e1001965. doi:10.1371/journal.pbio.1001965

Stewart, J. L., Coan, J. A., Towers, D. N., & Allen, J. J. B. (2014). Resting and task-elicited prefrontal EEG alpha asymmetry in depression: Support for the capability model. *Psychophysiology*, *51*(5), 446–455. doi:10.1111/psyp.12191

Stothart, C., Boot, W., Simons, D., & Beyko, A. (2014). Action video game experience does not predict multiple object tracking performance. *Journal of Vision*, *14*(14), 353. doi:10.1167/14.10.353

Voss, M. W., Kramer, A. F., Basak, C., Prakash, R. S., & Roberts, B. (2010). Are expert athletes 'expert' in the cognitive laboratory? A meta-analytic review of cognition and sport expertise. *Applied Cognitive Psychology*, *24*(6), 812–826. doi:10.1002/acp.1588

Wagnild, G. M., & Young, H. M. (1993). Development and psychometric evaluation of the Resilience Scale. *Journal of Nursing Measurement*, *1* (2), 165–178.

Wang, F., Tanaka, M., & Chonan, S. (2008). Visualization of short-term HRV as an index for mental stress evaluation. *Proceedings of SPIE - the International Society for Optical Engineering*. ICMIT 2007: Mechatronics, MEMS, and Smart Materials, Vol. *6794*, pp. 67943R.

Williams, A. M., & Davids, K. (1998). Visual search strategy, selective attention, and expertise in soccer. *Research Quarterly for Exercise and Sport*, *69*(2), 111–128. doi:10.1080/02701367.1998.10607677

Worden, M. S., Foxe, J. J., Wang, N., & Simpson, G. V. (2000). Anticipatory biasing of visuospatial attention indexed by retinotopically specific-band electroencephalography increases over occipital cortex. *The Journal of Neuroscience : The Official Journal of the Society for Neuroscience*, *20*(RC63), 1–6. doi:10.1523/JNEUROSCI.20-06-j0002.2000

Wu, S. (2008). Video game expertise and visual search and discrimination (Unpublished doctoral thesis). University of Toronto, Toronto, Canada.

Wu, S., & Spence, I. (2013). Playing shooter and driving videogames improves top-down guidance in visual search. *Attention, Perception, & Psychophysics*, *75*(4), 673–686. doi:10.3758/s13414-013-0440-2

Yamada, F. (1998). Frontal midline theta rhythm and eyeblinking activity during a VDT task and a video game: Useful tools for psychophysiology in ergonomics. *Ergonomics*, *41*(5), 678–688. doi:10.1080/001401398186847

About the Authors

Yue Ding is a Ph.D. candidate in School of Medicine, Tsinghua University, Beijing, China. She received a B.E. degree in Biomedical Engineering in 2010 from Dalian University of Technology and Science. Her research interests include neuroeconomics and the neural mechanism of auditory emotion and memory.

Xin Hu is a Master student in Department of Psychology, Tsinghua University. She received an LL.B. degree in International Politics in 2014 from University of International Relations. Her research interests include the neural mechanism of emotion and neuromarketing.

Jiawei Li is a Master degree candidate in Department of Psychology, Tsinghua University. She received a B.S. degree in psychology in 2015 from Tsinghua University. Her research interests include the neural mechanism of interpersonal communication.

Jingbo Ye is the chief eSports coach in both Tobegin Inc. and Keahoral Inc. He is specialized at training professional eSports athletes, including LOL.

Fei Wang is a postdoc fellow at Tsinghua University. He holds a Ph.D. degree in Social Psychology from Tsinghua University and a Master's degree in Personality and Social Psychology from Peking University. He is interested in using brain imaging techniques such as fMRI and EEG to study social behaviors.

Dan Zhang is an associate professor at Department of Psychology, Tsinghua University, Beijing, China. He received a B.E. degree in automation in 2005 and a Ph.D. degree in biomedical engineering in 2011, both from Tsinghua University. He was a postdoctoral fellow in School of Medicine, Tsinghua University from 2011 to 2013. His research interests include social neuroscience, engineering psychology, and brain–computer interfaces.

Appendix

Method

Visual Search

In the visual search test, the participants were required to detect whether there was a letter 'L' within a letter cloud of 'T' and respond with a button press. There were 5 levels of the difficulties based on the density of the letters, 20 trials for each level. The densities of the letters varied from 9 × 9 letter matrix to 17 × 17 letter matrix in the step of 2 × 2 letters. Only 60% of letters in the matrix were shown randomly. In half of the trials, there were all "T" letters on the screen. In the rest half trials, one "L" was hidden in "T"s, whose place was randomly chosen by MATLAB. The regression slope of the response cost along five difficulty levels was computed and taken as the behavioral result, with flatter slope indicates better visual search ability (Castel et al., 2005). Response cost was defined as the accuracy divided by response time (Cain, Landau, & Shimamura, 2012).

Simple reaction time

In the simple reaction time test, the participants were instructed to press a button as soon as possible when they detected a briefly presented small dot on the screen. During testing, red dots were shown with a random inter-trial-interval from 1.5 to 3.5 s. The average reaction time of 10 trials is calculated to characterize the participants' general response speed.

Mouse tracking

In the mouse tracking task, the participants used a mouse controlled red trigger to continuously track a randomly moving white dot on the screen. Each participant finished two trials. Each trial lasted for 20 s. The positions of the white dot and red target were recorded for each screen refresh. The refresh rate of screen was set to 60 Hz, ending with 2400 samples for each participant. Both the precision and stability were taken as the features of mouse tracking. The distance between dot and target was calculated for each sample point in the trial. Tracking precision was defined as the mean distance; tracking stability was defined as the standard deviation.

Flanker test

In the Flanker test, the participants reported the direction (blue arrow, pro-response trial) or opposite direction (yellow arrow, anti-response trial) of a centrally presented arrow with distracting arrows at both sides. On half of the trials, the outside arrows pointed to the same direction as the central target arrow (congruent trial), and on the other half of trials, the outside arrows pointed to the opposite direction (incongruent trial). Trials were also classified on the basis of the tasks of both the current and the previous trial; for example, for a pro-response switched trial, a pro-response was required in the current trial, whereas an anti-response had been required on the previous trial. Define the response cost as the accuracy divided by response time (Cain et al., 2012). The difference between the response cost of congruent trials and incongruent trials was taken as the features, as well as the task switch cost. Task switch cost only counted in the pro-response switched and anti-response switched trials.

Multi-object tracking

In the multi-object tracking task, the participants were asked to simultaneously track 2–7 moving dots among 16 moving dots for 7 s and reported the tracking results. For the 6 difficulty levels, each contained 12 trials. The number of effectively tracked dots was calculated by the following formula and taken as the behavioral result (Oksama & Hyönä, 2008):

$$m = n(2P - 1)$$

where m is the number of target dots, n is the number of targets, and P is empirically observed accuracy. The effective number of tracked items was m, corresponding to the first p that was larger than 0.5.

Implicit association test of achievement motivation

The implicit association test of achievement motivation consisted of five experimental blocks, with 20–40 trials per block. At the beginning of each trial, a stimulus word appeared, and participants were asked to rapidly judge whether the word belonged to the top-left or top-right category by pressing the "E" or "I" keys. The stimuli and categories for each block were presented in Table A4.

The blocks 3 and 5 were the critical blocks. The implicit achievement score was calculated by subtracting the reaction time in block 3 from block 5.

Table A1. Behavioral factors' ANOVA and correlational results.

Task	Feature	ANOVA	*r*
Visual search	Accuracy slope	$F(2,30) = 1.18$	0.30
Simple reaction time	Reaction time	$F(2,30) = 1.65$	−0.33
Mouse tracking	Precision	$F(2,30) = 1.24$	−0.05
	Stability	$F(2,30) = 0.95$	−0.14
Flanker test	Response cost	$F(2,30) = 0.02$	−0.06
	Task switch cost	$F(2,30) = 0.49$	−0.05
Multi-object tracking	Tracked number	$F(2,30) = 3.72$*	−0.17
Implicit association test	Achievement intention	$F(2,28) = 0.74$	0.20
Big Five Inventory	Agreeableness	$F(2,30) = 1.37$	−0.24
	Conscientiousness	$F(2,30) = 1.62$	0.36*
	Neuroticism	$F(2,30) = 1.07$	0.11
	Openness	$F(2,30) = 0.02$	−0.27
	Extraversion	$F(2,30) = 0.13$	−0.18
Resilience scale	Resilience	$F(2,30) = 0.35$	−0.20

*$p < 0.05$.

Table A2. Neural factors' ANOVA results.

	Period			Event		
	Begin	Middle	End	Laning	Ganking	Battle
ECG	$F(2,28)$	$F(2,28)$	$F(2,28)$	$F(2,28)$	$F(2,28)$	$F(2,28)$
HR	1.55	0.51	1.71	0.44	1.72	1.13
HRV	1.31	3.34*	4.07*	1.15	4.94*	5.19*
RR	0.29	1.01	0.49	0.22	0.06	1.09
EEG	$F(2,23)$	$F(2,23)$	$F(2,23)$	$F(2,23)$	$F(2,23)$	$F(2,23)$
Midline	6.91**	7.61**	9.34**	4.75*	6.78**	7.61**
Asymmetry	2.18	0.16	0.52	7.14**	3.88*	19.70***
Occipital	1.94	2.41	3.57*	0.13	10.73***	2.79

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table A3. Neural factors' correlation coefficient.

		Period			Event		
		Begin	Middle	End	Laning	Ganking	Battle
ECG	HR	−0.25	−0.15	−0.21	−0.26	−0.29	−0.21
	HRV	−0.06	0.23	0.47*	0.08	0.28	0.39*
	RR	−0.04	−0.13	0.12	0.08	−0.02	−0.05
EEG	Midline	−0.27	−0.47*	−0.49*	−0.52*	−0.56**	−0.35
	Asymmetry	−0.08	−0.22	−0.08	−0.17	−0.77***	−0.50
	Occipital	−0.56	−0.67	−0.54	−0.70***	−0.69***	−0.53

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table A4. Stimuli and categories of each block in the achievement motivation IAT.

Block	Stimuli	Categories
1	24 Self/other words	Left: Self Right: Other
2	24 Success/failure words	Left: Success Right: Failure
3	24 Self/other words 24 Success/failure words	Left: Self + success Right: Other + failure
4	24 Success/failure words	Left: Failure Right: Success
5	24 Self/other words 24 Success/failure words	Left: Self + failure Right: Other + success

Big Five Inventory

The Big Five Inventory (BFI; John & Donahue, 1991) was employed to measure participants' personality. Participants read 44 statements and rated their degree of agreement using a 7-point Likert-like scale from 1 = *totally disagree* to 7 = *totally agree*. Five dimension scores of agreeableness, consciousness, neuroticism, openness, and extraversion were calculated by summing up the ratings of respective items (reversed-scored when necessary). The alpha coefficients for the five dimensions were .54, .58, .75, .74, .75, respectively.

Resilience Scale

The Resilience Scale (RS; Wagnild & Young, 1993) was employed to measure participants' resilience to stress. Participants read 25 statements and rated their degree of agreement using a 7-point Likert-like scale from 1 = *totally disagree* to 7 = *totally agree*. The resilience score was calculated by summing up the ratings of respective items. The alpha coefficient for the scale was .80.