Article

Cognitive and Behavioral Correlates of Achievement in a Complex Multi-Player Video Game

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Abstract
Over the past 30 years, a large body of research has accrued demonstrating that video games are capable of placing substantial demands on the human cognitive, emotional, physical, and social processing systems. Within the cognitive realm, playing games belonging to one particular genre, known as the action video game genre, has been consistently linked with demands on a host of cognitive abilities including perception, top-down attention, multitasking, and spatial cognition. More recently, a number of new game genres have emerged that, while different in many ways from "traditional" action games, nonetheless seem likely to load upon similar cognitive processes. One such example is the multiplayer online battle arena genre (MOBA), which involves a mix of action and real-time strategy characteristics. Here, a sample of over 500 players of the MOBA game League of Legends completed a large battery of cognitive tasks. Positive associations were observed between League of Legends performance (quantified by participants' in-game match-making rating) and a number of cognitive abilities consistent with those observed in the existing action video game literature, including speed of processing and attentional abilities. Together, our results document a rich pattern of cognitive abilities associated with high levels of League of Legends performance and suggest similarities between MOBAs and action video games in terms of their cognitive demands.

Keywords
action video games; cognitive demand; individual differences; MOBA video games

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1. Introduction

There is a long history of interest in the cognitive, emotional, physical, and/or social demands that are inherent in complex real-world experiences. As one possible window into this issue, many disparate sub-domains within psychology have explored the extent to which individuals' performance on highly multifaceted tasks can be predicted, at least partially, by a set of more primitive abilities or traits (Bowman, 2018; Brown, Zatorre, & Penhune, 2015; Titz & Karbach, 2014; Voss, Kramer, Basak, Prakash, & Roberts, 2010). Here, one general line of reasoning has been that if individuals who are top performers on a given complex task show advantages in a set of more primitive abilities, one possible reason for that relation is that the complex task places demand on those more primitive abilities. In other words, if the complex task places demand on certain abilities, individuals who are

higher in those abilities will perform better on the complex task than individuals who are lower in those abilities (noting of course, that other possible causes exist for such a relation).

The complex experience of interest in the current work is video game experience. Essentially, as soon as the video game medium came into popularity, correlational studies were already being performed demonstrating enhanced cognitive abilities in video game players relative to non-players (Gagnon, 1985; Griffith, Voloschin, Gibb, & Bailey, 1983). The early work in this domain often considered video games as a unitary activity and contrasted "individuals who commonly played video games" against "individuals who did not play video games." Yet as the video game industry evolved, reasonably distinct genres of video games emerged. Importantly, there has been evidence indicating that these genres differ in terms of their cognitive demands. In particular, one genre, known as the "action video game" genre (Green & Bavelier, 2003), has received the majority of the interest in the field of cognitive psychology. Action video games have been defined as games that require players to attend to a rapidly changing and highly cluttered environment as well as to make accurate decisions under time pressure as they engage with a wide array of incoming stimuli (Cardoso-Leite, Joessel, & Bavelier, in press; Spence & Feng, 2010). Prototypical examples of the action genre are first- or third-person shooter games. The proposal that action video games place extreme demands on speed of processing and attention in particular has been supported by the consistent finding of enhanced performance on, for instance, speed of processing and attentional control tasks in action gamers as compared to non-gamers (Appelbaum, Cain, Darling, & Mitroff, 2013; Colzato, van Leeuwen, van den Wildenberg, & Hommel, 2010). This correlational work has been further supported and augmented by intervention studies that have demonstrated that long-term training on action video games can enhance those core constructs (Feng, Spence, & Pratt, 2007; Strobach, Frensch, & Schubert, 2012; for recent meta-analyses on both expert/novice designs and intervention designs see, Bediou et al., 2018).

Much of the cognitive psychology literature on video games has been predicated on the idea that action video games were relatively unique in terms of their cognitive demands (at least as compared to many of the slower and more deliberate game genres of that period, such as turn-based strategy games or turn-based role-playing/fantasy games). Yet the past fifteen years have seen dramatic changes in the commercial video game landscape. For instance, over this time period, various new "hybrid" genres, that mix elements from the action genre along with one or more other genres, have come into increasing prominence (Dale & Green, 2017b). As an example, the majority of role-playing games (RPGs) today perhaps best fit within what is known as the action-RPG genre (Dale, Kattner, Bavelier, & Green, 2019). Action-RPG games include a mixture of traditional RPG el-

ements (e.g., skill progression trees, dialogue, etc.) and traditional action elements (e.g., first-person shooter or third-person shooter combat). Similarly, strategy games today are typically real-time, rather than turn-based. Accordingly, it has been suggested that these new hybrid genres, like the games that have traditionally been labeled as "action video games," also involve substantial cognitive demands. Consistent with this proposition, players of both the action-RPG and real-time-strategy genres have been observed to have many similar enhancements in speed of processing and cognitive control, as do avid action video game players (Dale & Green, 2017a; Dale et al., 2019; Kim et al., 2015). Furthermore, although there are fewer intervention studies on these new game genres, the studies that do exist have suggested that this relation is causal (Basak, Boot, Voss, & Kramer, 2008; Glass, Maddox, & Love, 2013).

Another new video game genre, one that has received comparatively little attention in the cognitive literature to date, is the primary interest of the current article—the multiplayer online battle area (MOBA) genre. Games that fall under the MOBA genre label have sometimes been referred to as action real-time strategy games. This latter label underscores the fact that MOBA games have components that share similarity with both the action video game genre and the real-time strategy game genre. One prominent example of the MOBA genre is the game League of Legends. At the start of a League of Legends game, players are divided into two teams consisting of between 3 to 5 individuals. As is true in first- and third-person shooter games, each player controls a single character called a "champion." Each champion has a unique combination of base abilities and attributes that make them more or less suitable for different styles of gameplay. For example, some champion's attributes and abilities make them particularly adept when fighting at close range with their enemies. Others are more suited for fighting from a distance or for healing and shielding their fellow teammates. Like many real-time strategy games, matches begin with the two teams on opposite sides of a map where their home base is located. Bases are connected across the diagonal of the game board by three "lanes." These lanes are initially the only part of the board with clear visibility. Players use their champions to attempt to destroy the opposing team's base. In order to reach the opposing team's base, the players must work together to destroy defensive structures, as well as to kill members of the opposing team and various non-player enemies. Through this process, players gather resources that they can allocate in various ways to strengthen their champions or team.

Successful MOBA play therefore appears to involve many of the same cognitive demands that have been previously identified in action video games. MOBA players must act in cluttered and ever-changing game environments, they must constantly and efficiently switch between more focused attentional states (i.e., focus on just their champion) and more diffuse attentional states (e.g.,

taking in the entire game map), and they must do so under significant time constraints given the real-time nature of the game. Yet, empirical data explicitly showing such a link between MOBA play and cognitive demand is currently lacking.

Assessing whether MOBA games may have similar speed of processing and cognitive control demands as action games has clear value for the field going forward. Indeed, nearly every theoretical perspective that underlies the use of video games as cognitive training platforms emphasizes the role of various cognitive demands in the training games as the key to a successful intervention. Yet, in the literature to date, genre and cognitive demands remain highly confounded because the game genres that have been used to place sustained load upon the cognitive system have nearly always been action games. Therefore, finding video game types that place similar load upon the cognitive systems as do action video games opens up new options for testing the key causal hypotheses in the domain.

Here, we sought to identify cognitive and behavioral correlates of performance in League of Legends. Given that MOBAs are commonly considered a blend between action games and real-time strategy games, the majority of our a priori expectations were derived from the previous expansive literature on associations between action video game experience and cognitive performance, as well as the considerably smaller body of work on real-time strategy games and cognitive performance. In particular, as discussed above, most theory in the action video game domain has emphasized the load that action games place upon speed of processing and attentional abilities (Dye, Green, & Bavelier, 2009; Green & Bavelier, 2012). This theory is supported by empirical results documenting those particular sub-domains of cognition as being most strongly impacted by action video game play (Bediou et al., 2018). Thus, many of the tasks utilized here assess these particular cognitive skills (e.g., a simple reaction time task as a measure of speed of processing; the multiple-object tracking (MOT) task as a measure of attentional control). Furthermore, a recent theoretical perspective has argued that improvements in speed of processing and attentional control should, in turn, promote the ability to learn, especially when it comes to tasks that require integration of information through time and the discovery of statistical structure (i.e., should promote "learning to learn"; Bavelier, Green, Pouget, & Schrater, 2012). Given this theoretical perspective, we hypothesized that high League of Legends performers should also show an edge at a visual statistical learning (VSL) task (i.e., where one must learn to detect certain statistical regularities) and in a reinforcement learning task (i.e., where one must quickly learn reward statistics in order to strike the right balance between exploration and exploitation). Finally, the last task in our cognitive battery was chosen based upon a recent empirical paper on League of Legends players specifically, which found that League of Legends performance was associated with fluid intelli-

gence (Kokkinakis, Cowling, Drachen, & Wade, 2017). We thus employed a deductive reasoning task that, while not a true fluid intelligence task, correlates with fluid intelligence and was short enough to fit in our extensive online battery. We note that in addition to these cognitive measures, we also took a variety of measures of personality traits, internal motivations, and mental health. Given the emphasis of this thematic issue on demand, we chose to focus the main article on the relations between League of Legends performance and cognitive abilities (the personality, motivations, and mental health measures were taken based upon previous research in, for instance, more social or clinical literatures). However, these other measures are described and reported in full in the Appendix (see also Table 1 for full list of measures).

2. Methods

2.1. Participants

Participants were recruited directly by the developer and publisher of League of Legends, Riot Games. Potential participants received a message that explained the study and directed interested participants to an online portal where the studies were run. A total of 1216 individuals initially enrolled in the study. From this initial pool of participants, 549 completed all three sessions of the study, although not every participant completed each task satisfactorily (see next sections for session details). Of these participants, 512 identified as male and 31 of these participants identified as female (the remainder preferred not to respond). Participants ranged in age from 18 to 56 years old, with a mean age of 23.6 years. Players were compensated for their participation with Riot Points, which is the in-game currency of League of Legends (i.e., Riot Points can be used to buy new champions, other in-game boosts, etc.).

2.2. Measure of League of Legends Performance

League of Legends players are rated according to their performance in a similar manner to an Elo rating system, which quantifies the probability that one player will beat another player. Because this rating is utilized in-game to automatically assign players to teams in such a way that the two teams have players of roughly equivalent skill, this rating is referred to as the "matchmaking rating" (MMR). After losing, especially to lower rated players, players may drop in their MMR; conversely, winning matches, especially against higher rated players, may result in an increase in MMR. There were 33 participants with missing MMR data, resulting in a total of 516 participants in our main analyses.

2.3. Overview of Tasks and Questionnaires

Participants completed three online sessions (see Table 1). These sessions involved answering question-

Table 1. The tasks and surveys completed by session.

Session 1	Session 2	Session 3
General demographics survey (age, gender, education, language, Socioeconomic Status (SES)	MOT task	Arrow task
State-trait anxiety index	Backwards digit span	VSL
Beck depression inventory	Odd-one-out task	Continuous performance test (CPT)
Big 5 personality inventory	Reinforcement learning task	Creative foraging task
Revised competitiveness index	Behavioral Inhibition System (BIS)/ Behavioral Activation System (BAS)	Video game addiction survey
	Adult ADHD scale	
	Need for cognition scale	

naires that evaluated aspects of personality and/or quantified certain lifestyle habits, and completing tasks designed to assess different cognitive capacities. The three sessions took on average approximately two hours in total to complete. Participants logged into the online portal via a unique login that was linked to their Riot ID (so that they could be compensated). All data collection was performed via this portal. The tasks/questionnaires were divided into separate sessions mainly to provide natural stop points if participants could not devote a full two hours at once to the tasks or otherwise needed a break (i.e., if they wanted to stop after one session and return to start the following session at a later time).

2.4. Measures of Cognitive Control

2.4.1. Multiple-Object Tracking Task

The MOT task is commonly utilized to measure attentional control (Yung, Cardoso-Leite, Dale, Bavelier, & Green, 2015). On each trial, 16 moving circles—some blue (targets) and some yellow (distractors)—appeared within a circular aperture. After two seconds, the previously blue circles switched to yellow making them visually indistinguishable from the distractors. Participants were told they needed to keep track of the previously blue circles. After four seconds, the circles froze in place and one circle was cued by turning white. The participant was then asked to indicate whether this circle was one of the initially blue target circles. The number of target circles varied between one and six and were presented in an intermixed fashion. The one target and six target conditions were each presented five times, while the two-through-five target conditions were presented ten times each, for a total of 50 trials per participant. To assess performance, we first removed reaction time outliers (reaction times less than 100ms or greater than 10000ms). We then calculated an inverse efficiency metric, defined as the mean reaction time (in seconds) of correct responses divided by the proportion of correct responses.

2.4.2. Continuous Performance Test Task

A CPT task (Rosenberg, Noonan, DeGutis, & Esterman, 2013) was employed as a measure of the ability to control/sustain attention through time. Participants were presented with a series of grayscale images of city and mountain scenes at the center of the screen. The images gradually transitioned from one to the next over the course of 800ms via linear pixel-by-pixel interpolation. Participants were instructed to press the space bar for each image of a city, and withhold any button presses for images of a mountain. 90% of all stimuli were of cities. To measure performance, we computed the sensitivity (d') score for each participant, calculated as z(hit rate) − z(false alarm rate). Note that to account for several participants being at perfect performance, we calculated the hit rate as (number correct + 0.5)/(total trials + 1). We excluded any participants with a negative d-prime, resulting in a total of 499 included participants.

2.4.3. Backwards Digit Span Task (Backwards Span)

The backwards digit span task was developed by Cambridge Brain Sciences (www.cambridgebrainsciences.com) to measure working memory. On each trial, participants were presented with a sequence of digits, shown one at a time (1000ms presentation followed by 500ms blank). After the last digit, they were asked to report the sequence they saw in reverse order by typing the digits on their keyboard. Feedback was given after each trial. The task was adaptive such that after a correct response, the span (number of digits) increased by one, while after an incorrect response, the span was decreased by one. Participants started the task with a span of four digits. Participants continued with the task until they produced three incorrect responses. Performance was measured as the mean number of digits across all correctly remembered sequences. We excluded participants with a score of zero span, resulting in 476 included participants.

2.5. Speed of Processing Measure: Arrow Task

The arrow task (Dale & Green, 2017a) was designed to assess simple speed of processing without the need to learn arbitrary button mappings. At the beginning of each trial, a tone was played for 1.75 seconds. This was followed by a variable delay period, ranging from one to two seconds (mean was 1.5 seconds). At the end of the delay period, an arrow was displayed, pointing either leftwards or rightwards. Participants were asked to press the arrow key on the keyboard corresponding to the arrow direction as quickly and accurately as possible. Participants were given six practice trials, and 60 test trials. We measured performance with an inverse efficiency metric calculated as the mean reaction time (in seconds) of correct responses divided by the proportion of correct responses, excluding reaction time outliers (reaction times less than 100ms or greater than 2000ms). A total of 516 participants completed this task.

2.6. Deductive Reasoning Measure: Odd-One-Out Task

The odd-one-out task, developed by Cambridge Brain Sciences (www.cambridgebrainsciences.com), was used to assess deductive reasoning. Importantly, performance on this task is also quite correlated with fluid intelligence. On each trial, participants were presented with nine sets of shapes, with each set varying in properties such as color, shape, and number of items. Participants were tasked with finding the set that was the most different from the others. They had three minutes to complete as many trials as they could. Early in the task, the odd one out was obvious (e.g., differed from the others in one parameter). As the task increased in difficulty, participants were tasked with taking several properties into account at the same time. Feedback was given after each trial. The final dependent measure was calculated as the number of correct responses made, minus the number of incorrect responses. We excluded participants with a score of less than −20, resulting in 508 included participants.

2.7. Learning Measures

2.7.1. Visual Statistical Learning

The VSL task (Siegelman, Bogaerts, Christiansen, & Frost, 2017) probes the ability to learn spatio-temporal patterns (often implicitly). Participants began the experiment with a 10-minute familiarization phase during which they viewed a collection of 24 abstract shapes in a continuous stream (shapes appeared for 800ms, with a 200ms break in between). Within the stream, and unbeknownst to the participants, the shapes were organized into triplets, each of which were presented 24 times. After familiarization, participants completed a testing phase. The testing phase began with a 34-trial block to measure pattern recognition. Participants were asked to select the patterns with which they were most familiar.

After the recognition block, participants were asked to complete an eight-trial pattern completion block. Here they were shown a triplet with one item missing and were asked to select the shape that best-completed the pattern from the available options. The final dependent measure was the total number of correct responses across trials.

2.7.2. Reinforcement Learning Task

The reinforcement learning task we employed (Dale, Sampers, Loo, & Green, 2018) required participants to quickly learn reward statistics in order to strike the right relative balance between exploring (i.e., searching out new information) and exploiting (i.e., taking advantage of already obtained information). Participants were presented with a 10 × 5 grid of rectangular boxes on a grey background. At the trial start, each of the 50 boxes contained three question marks ("???"). When the participant clicked on a box, the question marks were replaced by a point value, which remained in place for the entirety of a trial, and that point value was added to the participant's score. Point values were generated by first simulating a normal distribution, then exponentiating the simulated values to produce a log-normal distribution. Those values were put into 75% of the boxes, with the remaining 25% of the boxes set to zero value. Participants were told that on each trial they had 50 total "clicks" and they were asked to accrue as many points as they could. The task thus required the participants to decide at each moment whether they wanted to click on a box with an unknown value (i.e., to explore) or to click on the uncovered box with the highest value (i.e., to exploit). Participants were given three total trials. The exploration score was the number of unique boxes clicked across all three trials. A total of 516 participants completed this task.

3. Results

3.1. Data Pre-Processing

Shapiro-Wilk tests indicated that the cognitive measures were not normally distributed, but were instead positively or negatively skewed. Given that our analytic approach assumed normally distributed data, we first estimated and applied one-parameter box-cox transformations to each linear model (Box & Cox, 1964). In brief, the box-cox transformation is defined as:

$$T(y) = \frac{y^{\lambda} - 1}{\lambda}$$

The procedure thus finds the value of lambda that maximizes the normality of the resulting data. Given that some measures included negative values, the box-cox with negatives transformation described in Hawkins and Weisberg (2017) was used, in order to adjust y to be strictly positive. The lambda values utilized are listed in Table A1. We will note that alternative methods of trans-

forming data so as to produce more normal distributions (including Tukey's Ladder of Powers) provide qualitatively similar results. The same was true when employing non-parametric quantile, ranked regression and a general linear model approach using a gamma link relating MMR to cognitive skills while controlling for age (see Table A3), which likewise gave similar results to our parametric tests. All transformations were used with the *car* package in R.

3.2. Testing Predicted Relations with Cognitive Abilities

We chose to perform separate linear regressions for each dependent measure (rather than, for instance, utilizing a larger multivariate model) for a number of reasons. First, previous research predicted significant positive relations between League of Legends ability and each of the cognitive tasks that were employed. Thus, separate analyses were most appropriate for testing those specific predictions (e.g., a multivariate model tests something other than those specific predictions). Second, not only is there no a priori reason to combine across these tasks, for most of the tasks, there is in fact reason to believe that they do not tap exactly the same cognitive construct (i.e., there are many sub-processes falling under the broad label of "cognitive abilities," but they are not necessarily all theoretically linked to one another). For interested readers however, we report correlations across measures in the Appendix (Figure A1). We note that for each of the reported analyses below, the model included controlling for age (as age was significantly and strongly negatively correlated with MMR in our sample, see Table A2, in the Appendix). Given the paucity of females though (making up only around 5% of the sample), it was not possible to control for gender. Analysis of only male participants resulted in qualitatively similar results. We also performed an alternative analysis using general linear models, with comparable results (Appendix, Table A3).

All of our a priori predictions were born out in the data, with small to medium effect sizes and with some variations across cognitive constructs (Table 2). In particular, the strongest relations were seen between League of Legends performance and the arrow task, MOT task, and the reinforcement learning task (with effect sizes roughly in line with those observed previously in a meta-analysis of action video games; Bediou et al., 2018). Intermediate effects were observed for the CPT task, the backwards span task, and the odd-one-out task. The VSL task effect was the weakest, just reaching statistical significance. Importantly, for the reinforcement learning task, although our primary measure was exploratory choices, MMR was also positively associated with greater overall reward gained (i.e., fewer exploratory choices meant a tendency to learn the reward structure quickly and shut off exploration so as to maximize points gained).

4. Conclusions

As expected, greater levels of performance in League of Legends was associated with enhancements in both speed of processing and cognitive control abilities. Indeed, the two strongest relations with League of Legends skill were with the arrow task and the MOT task. Differences in speed of processing and in attentional control are amongst the more consistently reported observations in the action game literature. For instance, in terms of speed of processing, one review found that action gamers respond on average approximately 10% faster than non-gamers across a wide range of tasks (Dye et al., 2009). And in terms of attentional control, these abilities were associated with the largest effect sizes in a recent meta-analysis (Bediou et al., 2018). Therefore, while simple visual inspection of League of Legends gameplay might have suggested that substantial cognitive demands are involved, these empirical results strengthen the case that similar demands are placed on at least some cognitive sub-systems as do more traditionally identified action video games.

Outside of the speed of processing and attentional control domains, several other expected relations were

Table 2. Regression values between League of Legends MMR and cognitive abilities.

Category	Measure	F-value (df1, df2)	p-value (two-tailed)	Partial R²
Cognitive control	MOT	14.03 (1,513)	< .001	.027
	CPT	6.22 (1,496)	.013	.012
	Backwards digit span	6.56 (1,473)	.011	.014
Speed of processing	Arrow task	26.63 (1,513)	< .001	.049
Deductive reasoning	Odd-one-out	7.21 (1,505)	.007	.014
Learning	VSL task	3.70 (1,513)	.055	.007
	Reinforcement learning task	19.38 (1,513)	< .001	.036

Notes: All analyses controlled for age, thus the F-value, associated p-value, and Partial R² are for the given measure after controlling for age, not for the full model; the direction of the effects has also been standardized for all tasks except the reinforcement learning task such that positive relations mean that higher levels of MMR go with better cognitive task performance (i.e., faster and/or more accurate); for the reinforcement learning task the negative relation indicates that higher levels of MMR go with lower levels of exploratory choices—as noted in the main text however, this resulted in overall more points earned in the task.

observed. First, consistent with previous work showing a relation between League of Legends performance and fluid intelligence (Kokkinakis et al., 2017), we observed a similar relation between League of Legends performance and deductive reasoning, although it was the weakest of the cognitive effects. Our data also supported the recent proposal that one knock-on effect of the improvements in speed of processing and attentional control seen in action video game play should be in the ability to learn to perform new tasks. Indeed, higher levels of League of Legends performance was associated with both better VSL and better performance on a reinforcement learning task, with the latter being numerically stronger than the former (Bavelier, Bediou, & Green, 2018; Bavelier et al., 2012).

Going forward, there are a number of potential follow-up purposes that can be explored. For instance, in certain areas of psychology, a great deal of effort has been spent in identifying relations between basic cognitive, perceptual, and motor abilities and the probability that an individual will reach satisfactory levels of performance in certain occupations, such as military pilots or unmanned drone operators (Lintern & Kennedy, 1984; McKinley, McIntire, & Funke, 2011). Because training individuals in many complex occupations can be time-consuming and costly, it often makes sense to pre-select for training only those individuals whose basic ability set suggests that they have a high likelihood of eventual success. Because MOBAs, and League of Legends in particular, are currently one of the most popular e-sport genres/games (Campbell, Toth, Moran, Kowal, & Exton, 2018), a greater understanding of the cognitive underpinnings of performance could potentially be utilized in similar ways as, for example, 40-yard dash times in athletics recruitment.

A second related follow-up would be to examine the potential for interventions meant to improve performance on the cognitive abilities identified here to in turn improve performance in League of Legends. Such an approach, for instance, underpins much of the literature on cognitive training meant to enhance performance in educational settings (Titz & Karbach, 2014). Correlational studies have repeatedly identified a number of core cognitive abilities as being associated with academic success as, for example, fluid intelligence, working memory, executive functions, etc. (Alloway & Alloway, 2010). The goal of many interventions in this domain is therefore to enhance those cognitive functions with the expectation that this will, in turn, enhance academic performance (i.e., testing the causal link). Similar future work could thus examine, for example, whether dedicated speed of processing training serves to enhance performance on MOBA games.

A third possibility for follow-up work is to examine the potential for League of Legends training itself to enhance the associated cognitive functions. This is, in essence, the inverse of the goal above. Indeed, the purely correlational methodology employed in the cur-

rent work does not allow the directionality of the various associations to be inferred (or even whether the associations are causal in nature). Most contemporary theories on how one might enhance core cognitive abilities suggest the need to put consistent load upon those constructs (Singley & Anderson, 1989). While simple tasks may place load upon the constructs initially (and thus can be good measurement tools), long-term practice with such tasks can quickly result in automaticity, which necessarily entails a reduction in the associated cognitive load. For this reason, it has been argued that complex tasks may be better for training purposes than simpler tasks (Anguera & Gazzaley, 2015; Bavelier et al., 2018; Moreau & Conway, 2014); video games such as League of Legends would certainly qualify as complex.

We note that while the sample size in the current work is large, given the novelty of the approach, caution is warranted with regard to overinterpreting the results. While there were strong a priori predictions for many of the associations, even larger confirmatory work is likely warranted before moving on to other follow-up work based upon these results. Furthermore, single cognitive measures are, in practice, essentially never process pure (Engle, Tuholski, Laughlin, & Conway, 1999). In other words, even tasks that have been simplified as much as possible so as to load primarily one particular cognitive function, rarely do so perfectly. Thus, future work should expand the battery in such a way that would allow latent variable-type analyses to be conducted so as to better understand the relation between League of Legends performance and cognitive constructs, rather than the relation between League of Legends performance and individual cognitive tasks. Finally, there is strong interest, not just in terms of the predictors of asymptotic levels of performance in complex skills, but in predictors of the rate at which complex skills are learned. Thus, future work could also examine predictors of the full progression from novice player to asymptotic performance.

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Conflict of Interests

The authors declare no conflict of interests.

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Appendix

1. Methods for General Linear Model

We first entered MMR and AGE variables, and then used generalized linear models (with the canonical link function corresponding to a gamma distribution) where main effects of MMR and AGE predict the variety of cognitive skills.

Table A1. Box-cox transformations utilized to make data normally distributed.

Task	Lambda
Arrow Task	−2.17
Continuous Performance Test	1.77
Reinforcement	0.31
Multiple Object Tracking	−0.32
Backwards Span	−2.28
Odd-One-Out	1.56
Visual Statistical Learning	0.69

Table A2. Regression values between League of Legends MMR and age.

Measure	F-value (df1, df2)	p-value (two-tailed)	R^2
Age	79.93 (1,514)	< .001	.135

Figure 1. Values from general linear model between League of Legends MMR and cognitive abilities.

Table A3. Regression values between League of Legends MMR and age.

Category	Measure	t-value	p-value (two-tailed)	Effect Size r
Cognitive Control	Multiple-Object Tracking	3.83	< .001	.175
	Continuous Performance Test	−2.17	.031	−.098
	Backwards digit span	−2.16	.031	−.067
Speed of Processing	Arrow Task	4.86	< .001	.205
Deductive Reasoning	Odd-One-Out	−2.51	.012	−.108
Learning	Visual Statistical Learning Task	−1.96	.050	−.090
	Reinforcement Learning Task	4.56	< .001	.206

2. Additional Measures Taken

2.1. Methods for Additional Questionnaires Taken in Battery

2.1.1. Big 5 Personality Inventory

We utilized a ten-item questionnaire to assess the Big-5 personality dimensions (two items for each of the five dimensions: openness to experience, conscientiousness, extraversion, agreeableness, neuroticism; one item for the "low" end of the dimension, one item for the "high" end of the dimension; Rammstedt & John, 2007). Each question asked the participant to indicate how well a particular statement described them on a five-point Likert scale. The final dependent measures were calculated by adding the value of the response in the "high" question for a given factor to six minus the value of the response in the "low" question for that factor. Due to incomplete responses, 515 participants were part of the analysis.

2.1.2. Revised Competitiveness Index (Competitiveness)

The revised competitiveness index (Houston, Harris, McIntire, & Francis, 2002) probes the extent to which participants enjoy competition and/or show contentious competitive behavior (e.g., "I often try to outperform others"). Fourteen questions were answered on a five-point scale. The final dependent measure was the sum of the responses.

2.1.3. Behavioral Inhibition/Activation Scales (BIS–BAS)

The BIS/BAS scale (Carver & White, 1994) is used to assess what are commonly treated as two distinct motivational systems: Behavioral inhibition (tendency to avoid negative situations/punishment), and behavioral activation (motivation to achieve goals/receive positive outcomes). The questionnaire consists of 24 items to measure four sub-scales: One BIS sub-scale and three BAS sub-scales (drive; fun seeking; reward responsiveness). The final measures consisted of one measure for BIS and one for BAS created by summing over the respective sub-scales. 568 participants were counted, after excluding for missing MMR values.

2.1.4. Need for Cognition Scale

The Need for Cognition (short form; 18-item) scale (Cacioppo, Petty, & Kao, 1984) was utilized to assess the extent to which individuals seek out and enjoy difficult cognitive experiences (e.g., "I prefer complex to simple problems"). The final dependent measure was the sum of responses.

2.1.5. Creative Foraging Task

Our measure of creativity was a "creative foraging" task (Hart et al., 2017). Players were initially presented with ten green identical squares arranged in a horizontal line. They were then asked to create shapes by moving the squares to create other fully connected shape (squares are connected through a shared edge). Each movement of a square was considered a "step." They were told that their goal was to "explore the space of shifting shapes and discover those that you consider interesting and beautiful." At each step, they were allowed to save their current shape to a gallery by clicking a gray square at the top-right corner of the screen. After 15 minutes, participants were asked to choose the five most creative shapes from their gallery. This task produces a number of measures. For the current work we created an aggregate of the participant's exploration (measured as creating visually dissimilar shapes and spending more time between steps) and exploitation (creating visually similar shapes and spending less time between steps). Fewer participants completed this task, resulting in a total of 316 participants in our dataset.

2.1.6. State-Trait Anxiety Scale (Anxiety)

The questionnaire, adapted from the State-Trait Anxiety Inventory, Trait Version (Form Y; Spielberger, Gorsuch, Lushene, Vagg, & Jacobs, 1983) consisted of 20 questions answered on a four-point Likert scale that each addressed characteristics of anxiety (e.g., "I am nervous and restless"). The final dependent measure was the sum of responses.

2.1.7. Beck Depression Inventory II (Depression)

An 18-question version of the Beck Depression Inventory was utilized (Beck, Ward, Mendelson, Mock, & Erbaugh, 1961). Each question asked participants which of four possible answers best described their current state at that moment. Rather than giving a value answer, the inventory provides four responses that range in severity (e.g. "I don't feel disappointed in

myself"; "I am disappointed in myself"; "I am disgusted with myself"; "I hate myself"). The final dependent measure was the sum of the responses. Due to incomplete responses, 515 participants were part of the analysis.

2.1.8. Adult ADHD Self-Report Scale (ADHD)

We utilized Version 1.1 of the World Health Organization's Adult ADHD self-report scale (Spencer, Biederman, & Mick, 2007). Each of the six items in the scale asks participants to rate themselves on a five-point scale in terms of possible symptoms of ADHD (e.g., "How often do you feel overly active and compelled to do things, like you were driven by a motor?"). The final dependent measure was the sum of the responses. Due to incomplete responses, a total of 514 participants were included.

2.1.9. Video Game Addiction (VG Addiction)

The survey that was utilized (Eichenbaum, Kattner, Bradford, Gentile, & Green, 2015) included 13 questions modeled after the DSM-V criteria for pathological gambling, but applied to video game play (e.g. "In the past year, have you ever felt you could not stop playing video games?"). Participants could respond with "Yes" (coded as 1), "Sometimes" (coded as 0.5), "No" or "Don't Know" (both coded as 0). The final dependent measure was the sum of the responses.

2.2. Results for Additional Questionnaires Taken in Battery

Analyses between League of Legends MMR and various behavioral measures were conducted in a manner commensurate with those in the main manuscript; yet it is important to acknowledge these were exploratory (Table A2). Three of the relations were statistically significant without controlling for multiple comparisons (BIS, BAS, and extraversion). However, only BIS (higher levels of League of Legends performance going with greater behavioral inhibition) and extraversion (higher levels of League of Legends performance going with lesser extraversion) were significant after controlling for multiple comparisons (N = 14; critical p = .0036). We note that the strength of the various nulls is supported by the fact that other a priori expected trends, not relevant to the question of League of Legends performance, were observed in the data. For instance, certain personality traits are known to change with age (Roberts, Walton, & Viechtbauer, 2006) and these trends were consistently seen in our data (e.g., conscientiousness significantly increased with age; neuroticism, openness to experience and anxiety significantly decreased with age).

Table A4. Box-cox transformations utilized to make data normally distributed.

Task	Lambda
Extraversion	0.66
Conscientiousness	0.69
Agreeableness	1.48
Neuroticism	0.59
Open to Experience	1.16
Competitiveness	1.70
BIS	1.30
BAS	1.59
Need for Cognition	1.16
Creativity	−0.46
Anxiety	0.33
Depression	−1.05
ADHD	1.02
Video Game Addiction	0.06

Table A5. Regression values between League of Legends MMR and behavioral factors.

Category	Measure	F-value (df1,df2)	p-value (two-tailed)	Partial R^2
Personality	Extraversion	10.36 (1,512)	*.001	.020
	Conscientiousness	.98 (1,512)	.323	.002
	Agreeableness	.63 (1,512)	.428	.001
	Neuroticism	.75 (1,512)	.388	.001
	Openness to Experience	3.37 (1,512)	.067	.007
	Competitiveness	2.60 (1,513)	.108	.005
	BIS	10.52 (1,513)	*.001	.020
	BAS	6.38 (1,513)	.012	.012
	Need for Cognition	.060 (1,513)	.809	< .001
	Creativity	1.23 (1,276)	.267	.004
Mental/Clinical Health	Anxiety	.01 (1,513)	.907	< .001
	Depression	.61 (1,512)	.436	.001
	ADHD	.80 (1,510)	.327	.002
	Video Game Addiction	.40 (1,513)	.529	.001

Notes: All analyses controlled for age, thus the F-value, associated p-value, and partial R^2 are for the given measure after controlling for age. * denotes significant after controlling for multiple comparisons.
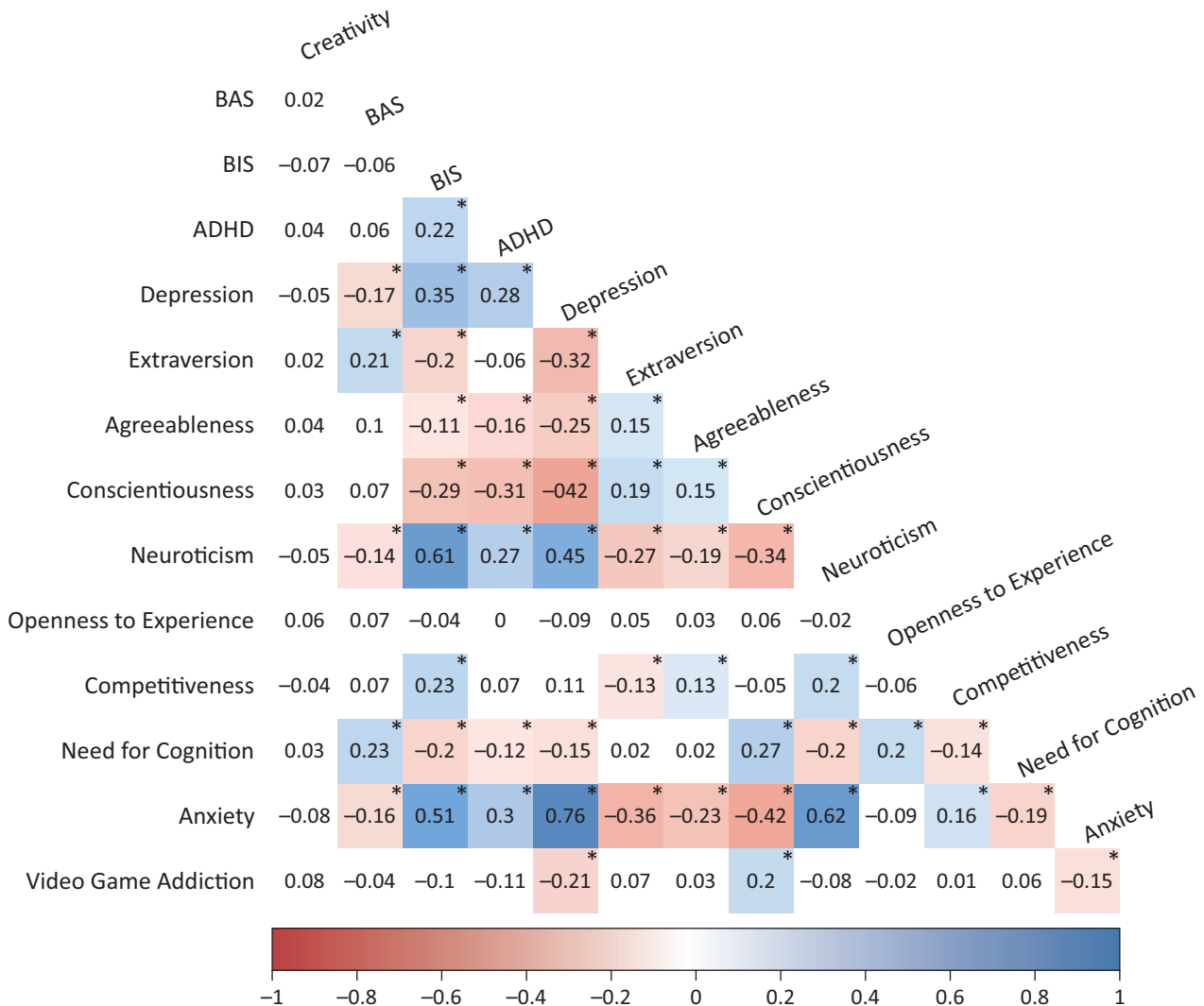

Figure 2. Correlation matrix of behavioral factors. Note: Asterisks indicate p < 0.01.

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