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Cognitive Styles are poor predictors of esports player's performance in League of Legends

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Abstract

Aim: Research on cognitive correlates of achievement in esports has started only recently. None of these studies focused on cognitive styles as a possible correlate of achievement, or player performance, in esports. Thus, the goal of the present study is to check whether cognitive styles (i.e., field-dependence - field-independence, reflectivity - impulsivity, and rigidity - flexibility of cognitive control) could predict performance in the game League of Legends, operationalised as in-game rank.
Methods and results: In total, 41 participants with different ranks in League of Legends were recruited. Each participant filled out the online form with general information about themselves and their experience in League of Legends. Participants completed three online tests: Stroop test for rigidity - flexibility style, Matching Familiar Figures Test for reflectivity - impulsivity style, and Gottschaldt Figures Test for field-dependence - field-independence style. Only the in-game experience, measured in years (for the whole sample) and in the total number of matches played during two seasons, predicted the in-game rank (measured for 34 participants).
Conclusion: Results of this study suggest that none of the explored cognitive styles; rigidity-flexibility, reflectivity-impulsivity or field dependence-field independence styles are predictors of player's performance in League of Legends and that experience is more important.

Keywords: League of Legends, cognitive style, performance, gaming skills, esports, MOBA games

Highlights

- Indicators of impulsivity - reflectivity style and field-dependence – field-independence showed moderate correlations with the experience measured in the number of ranked games played, but not with in-game rank
- Experience in years and the number of ranked matches could predict the in-game rank, whereas cognitive styles did not

Introduction

Studies that focus on players' performance and esports rather than gaming in a broad sense have emerged only recently. Himmelstein, Liu, & Shapiro (2017) conducted interviews with high-level competitive League of Legends players. The goal of their study was to explore which techniques are used by competitive esports players to achieve optimal performance and which obstacles are encountered by them. Specifically, respondents mentioned staying motivated, practicing individual skills, and relying on the team as possible ways to improve performance. Among encountered obstacles, they mentioned ineffective attentional control and communication, and confidence issues.

Other studies used numerous cognitive tasks to reveal cognitive correlates of achievement in League of Legends (LoL), one of the most popular esports titles. Li, Huang, Li, Wang, and Han (2020) found that top-ranking LoL players, which are 0.17% of global top players in the world have better executive control compared to average-ranking players with an equal amount of in-game hours. The tasks used in this study measured three aspects of executive control: impulsive control, interference control, and cognitive flexibility. It was shown that top-ranking players demonstrated higher impulsive control in a continuous performance test, and were better at cognitive flexibility and resolving interference in a Stroop-switching test. Authors provide two alternative explanations for their results: either top players were more motivated at training in-game skills and executive functions, or only those individuals with superior cognitive skills can achieve the highest ranking in the game. In a few other studies in-game rank in LoL could be predicted, to some extent, with fluid intelligence and rotation span of working memory (Kokkinakis, Cowling, Drachen, & Wade, 2017), spatial location memory (Bonny, Castaneda, & Swanson, 2016), visual spatial working memory and top-down attentional control (Valls-Serrano, De Francsico, Vélez-Coto, & Caracuel, 2022), cognitive flexibility (Valls-Serrano, De Francsico, Caballero-López, & Caracuel, 2022), and number of played matches (Röhlcke, Bäcklund, Sörman, & Jonsson, 2018). Number processing ability was also linked with the current in-game rank and the gain in it over time (Bonny & Castaneda, 2017).

Large and colleagues (2019) went even further. Researchers partnered with Riot Games, developers and publishers of LoL, to recruit more than 500 players for a large battery of surveys and cognitive tasks: Multiple-Object Tracking (MOT) Task, continuous performance test, reinforcement learning task, Big 5 personality inventory, arrow task, etc. Cognitive tests were used to measure cognitive control, learning, speed of processing, and deductive reasoning. According to the results of this large-scale study, the two strongest predictors of LoL skill were arrow task and MOT task, indicating, respectively, speed of processing and cognitive control as strongly related to in-game skill. The ability to perform new tasks and deductive reasoning were also associated with in-game performance, although the latter construct had the weakest effect.

All in all, the idea behind these studies is the following: performance in simple cognitive tasks, that assess particular cognitive skills (e.g. attentional control in MOT task), can predict performance in a complex task, which requires different cognitive skills (e.g. performance in an esports discipline). However, it is not understood by now how different cognitive styles affect the player's performance.

Cognitive Styles and Gaming

Cognitive styles are usually defined as a consistent individual's manner of cognitive functioning with respect to acquiring and processing information (Kozhevnikov, 2007). Three of the cognitive styles are among the most well researched in the context of gaming: field-dependence

- field-independence, reflectivity - impulsivity, and rigidity - flexibility of cognitive control (Hong et al., 2012; Alharthi et al., 2021; Bogacheva & Voiskounsky, 2015). **Field-dependent** persons have difficulties identifying a geometric shape in a complex background image. Conflicting patterns of their visual fields distract them. And vice versa, **field-independent** people complete this task much faster and easily overcome the influence of the visual field (Witkin, 1950). **Impulsive** participants tend to react quickly in situations of multiple decision-making without testing alternative hypotheses, while **reflective** participants are characterized by slower reaction time and with multiple hypotheses testing and correction (Kagan, 1966). **Rigid cognitive control** indicates difficulties in the transition from verbal to sensory-perceptual functions in the situation of cognitive conflict due to the low degree of their automation, while **flexible control** indicates the relative ease of such a transition (Gardner, Holzman, Klein, Linton, & Spence, 1959).

Although at present most cognitive scientists claim that cognitive styles are 'out of style', Sternberg and Grigorenko (1997) provide arguments for the future of cognitive styles as a concept. Firstly, they allowed uniting two fairly distinct psychological areas: cognitive psychology and personality, leading to a vast amount of research on individual differences in information processing. Secondly, cognitive styles were operationalized through various empirical tests providing objective measurement tools for psychologists. Third, by knowing features of a person's cognitive styles one might tell something about an individual's environments and the way he or she interacts with these environments. Finally, and most importantly for this study, cognitive styles were linked with school and job performance. For example, cognitive styles tests may significantly predict school achievements (Zhang, 2002; Kholodnaya, 2004), exam results (Riding & Caine, 1993; Sellah, Jacinta, & Helen, 2018), and may be used in the recruitment of pilots (Glicksohn & Naor-Ziv, 2016) and accountants (Gul, Huang & Subramaniam, 1992). In the context of non-video games, one small-sample study revealed that after 50-hours chess training female students demonstrated increased field-independence (Smith & Sullivan, 1997). Another study found a positive relationship between field-independence and decision making performance in snooker players (McMorris, Francis, MacDonald, & Priday, 1993). Thus, considering that esports is synonymously referred to as cognitive sport (Campbell, Toth, Moran, Kowal & Exton, 2018), using cognitive styles as a predictor of player performance might be of great use for the selection of the most prominent players in esports.

Not much attention has been drawn to the specifics of cognitive styles in gaming and, particularly, in esports. In one such study, a positive correlation was identified between digital jigsaw puzzle scoring and field-independence (Hong, Hwang, Tam, Lai, & Liu, 2012). In another study, Alharthi and colleagues (2021) focused on the effects of individual cognitive styles on collaborative gameplay. They tested each of the 54 participants to classify them as either field-dependent (FD), or field-independent (FI). Then, researchers split participants into three types of dyads, based on the cognitive style of each member: FD-FD, FD-FI, and FI-FI. Each dyad had to perform in a collaborative computer game, set up in an ecologically valid environment (i.e., a game cafe). It was shown that dyads with at least one FI player demonstrated increased team performance and experienced lower cognitive workload, while no difference was found for communication level and player's perceived performance.

Furthermore, gamers and non-gamers were demonstrated to differ in cognitive styles. Bogacheva and Voiskounsky (2015) in their study focused on three of the most popular cognitive styles: field-dependence - field-independence, reflectivity - impulsivity, and rigidity - flexibility of cognitive control. Researchers were particularly interested in the connection of cognitive styles with gaming activity (in hours per week) and preferred game type (online versus offline).

The authors concluded that high reflectivity and field-independence were significantly more common among gamers, especially offline gamers than among non-gamers. Besides, gamers, who played computer games for more than 12 hours per week, were characterized by the highest field-independence and flexibility of cognitive control, whereas less active gamers were the most reflective among all three groups. Although we find the used classification of games highly arguable and imprecise, Bogacheva and Voiskounsky (2015) provided a starting point to set new hypotheses and proved that cognitive style might be a prominent concept for research in the context of gaming. For the present study, we focused on one of the most popular esports titles in the world, League of Legends.

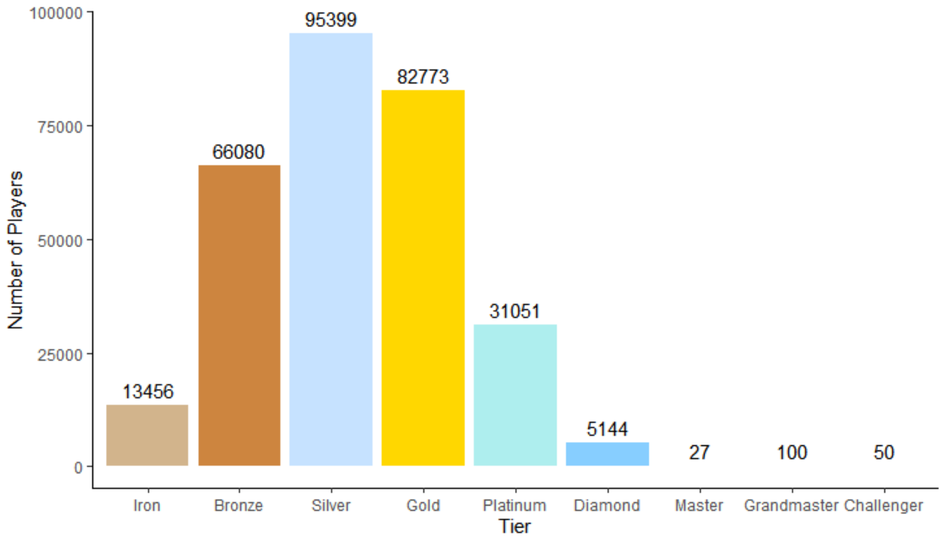
League of Legends

Multiplayer Online Battle Arena (MOBA) games share common features with both action video games and real-time strategies. One of the most prominent examples of MOBA games is League of Legends (LoL). In LoL, two teams of five players compete in matches that last about 20-35 minutes. Each player controls a unique character called a ‘champion’, which players choose before the match. Every champion has their own set of abilities and base attributes, which can be improved during the match in various ways, allowing players to find the most suitable style of gameplay. Moreover, each champion can be assigned a class and at least one position on a game map, which together determines the role of each player in a team, though this classification is not absolute. For instance, some champions are best at healing and shielding their teammates or fighting from a distance. Others might be specialized in breaking into battles first and taking a lot of damage.

The main goal of the match is to destroy the opposite team’s base. To achieve it, players have to accomplish various tasks during the match: kill members of the opposing teams, destroy defensive structures on the lanes, earn gold by killing non-player enemies on the lanes or in the jungle, etc. The resources acquired during the match are allocated to strengthen champions and team. The match ends either when one of the teams votes for surrender, or when one of the bases is destroyed.

In competitive games, matchmaking (i.e., an automated process of matching players to and against other players in a game) requires a reasonable measurement of player’s gaming skill. The gaming skills can be considered as a level of expertise in the game, and the LoL ranking system provides a tool for objective measurement of the relative gaming skill. The ranking system is based upon the Elo rating system which was initially developed for chess and then adapted to esports disciplines. Thus, the LoL ranking system divides players into nine rank tiers, from Iron tier to Challenger tier (see Figure 1 for the distribution of players across tiers). Each tier represents a different skill level and allows appropriate matchmaking.

Figure 1. Distribution of ranked LoL players on the Russian server by tiers (data for 18.05.2021, computed with Riot API)



Another important feature of esports games is that they can be regarded as complex cognitive tasks which require various cognitive abilities. Players must make quick decisions about whether they should perform some action or not. Attention should be distributed across the game interface so that the player receives enough information on the current situation. All the unnecessary information should be filtered and both the individual and team strategies should be adjusted during the match in accordance with the acquired information. Moreover, the proper representation of the game features (e.g., champion's characteristics, timing of game events) should be learned and used during the match. Additionally, some studies showed a similar aging trajectory of in-game performance with changes in fluid intelligence (Kokkinakis et al., 2017) and cognitive-motor performance (Thompson, Blair, & Henrey, 2014). Thus, esports games set high demands on many cognitive abilities, from visual attention to decision-making, which can highly vary between individual players of different age.

Present Study

The goal of the current study is to check whether cognitive styles are interrelated with the player's performance in the LoL game. The results of this study could help esports players to identify their strengths and weaknesses and to develop training programs that specifically target their cognitive styles. Additionally, understanding the relationship between cognitive styles and esports performance could help to better understand the role of cognitive styles in success in esports and other competitive domains – for example, in some way education can also be regarded as a competitive domain, and there is already evidence of the link between cognitive styles and educational attainment (e.g., see Kholodnaya, 2004; Zhang & Sternberg, 2006). On the other hand, these results could contribute to the discussion about cognitive styles as a concept and their place in modern psychology - whether they are rather a part of history now, or they can still be useful, since the theory behind the cognitive styles has been widely criticized for the previous decades (Zhang & Sternberg, 2006).

Specifically, three cognitive styles are studied among LoL players in this paper: field-dependence - field-independence, reflectivity - impulsivity, and rigidity - flexibility of cognitive control. The findings of Bogacheva and Voiskounsky (2015) provided evidence that more active gamers demonstrated higher field-independence and flexibility of cognitive control, while gamers in general were more reflective than non-gamers. Alharthi and colleagues (2021) also showed positive effect on performance when having at least one field-independent person in a team, while Smith and Sullivan showed that chess training increases field-independence in female students. These three styles were additionally associated with higher educational attainment before (see books by Zhang & Sternberg, 2006, and Kholodnaya, 2004). Interestingly, Li and colleagues (2020) also found better executive control in the top-ranking LoL players using Stroop task, although they used Chinese version of the task and reaction time with errors for the analysis, while not interpreting their results in terms of cognitive styles. Given that, we hypothesized that the more reflective style a person has, the more accurate decisions he or she makes since the mistakes made during the game might drastically change the course of the whole match. We also assume that more field-independent players would score a higher rank since they probably could be better in both micro- and macromanagement of the game due to better filtering of all the input information from the game. And lastly, higher flexibility of cognitive control might also be useful in filtering the input information and quickly attending to the most important aspects of it.

Research Hypothesis

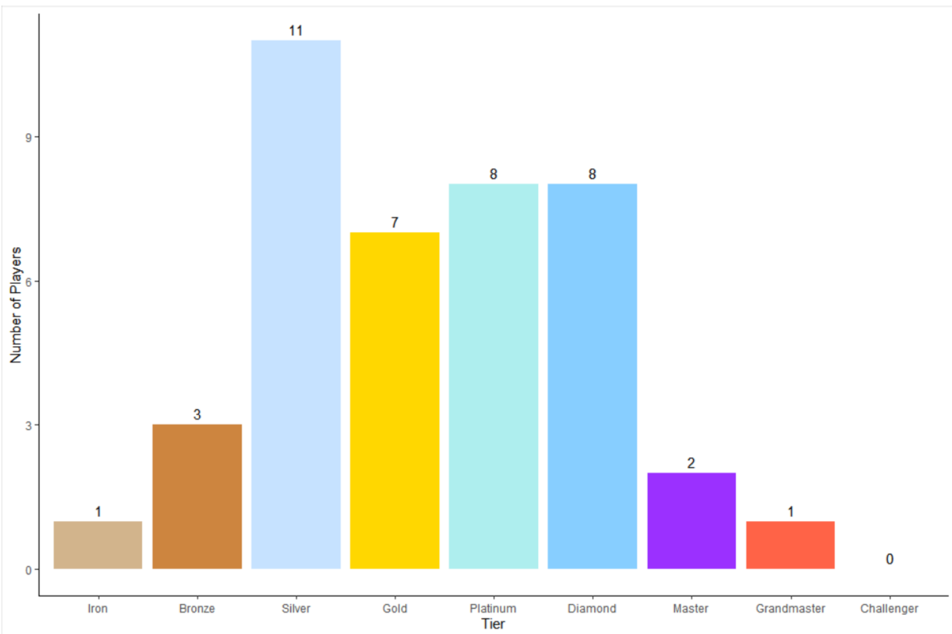
The higher *reflectivity/flexibility of cognitive control/field-independence* a player demonstrates, the higher *in-game rank* he or she has.

Methods

Participants

Participants were League of Legends players that reached any rank in the game season 2020 in the solo or duo queue (N=41, 34 male) and with an age range from 18 to 30. Participants were recruited via the social network VKontakte, gaming forums, and esports university societies. Seven of the participants from the previous non-related research (Sergeev, Timokhov, Baskakov, and Tsinevich, 2020) were invited to the current study, representing highly-skilled players and professional esports players, which are more difficult to recruit randomly. Importantly, however, the distribution of participants' ranks is slightly biased towards higher ranks (see Figure 2, general population distribution is in Figure 1) which is considered a limitation of our sample. At the end of the study, the interpreted results of the cognitive styles tests were sent as feedback to each participant.

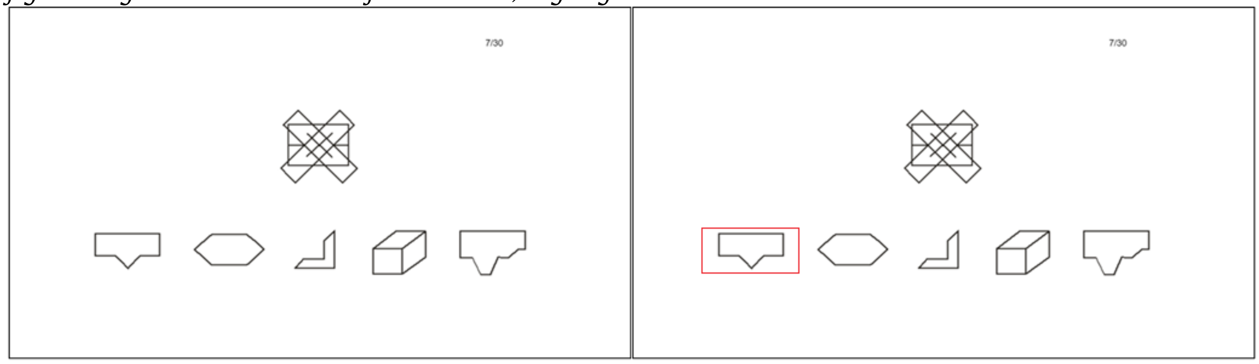
Figure 2. Distribution of cohort by tiers



Cognitive Styles Tests

For field-dependence - field-independence (FD-FI) assessment "Gottschaldt Figures Test" (2013) (GFT) was used. In GFT, participants have to find a simple form in a complex figure (see Figure 3). At the core of the task is the assumption that FD people are more subject to the influence of the external field, whereas FI people are influenced less by the external field. Thus, FD people are assumed to complete the task less successfully than FI people, show fewer correct answers and more time spent for the task. The version of GFT in this study includes 30 complex figures.

Figure 3. An example item from the Gottschaldt Figures Test (GFT). Left: the part at the center represents a complex figure, while one of the shapes in the bottom is embedded in the complex figure. Right: correct answer for the item, highlighted in red



Rigidity - flexibility of cognitive control was assessed with the well-known Stroop task (see "Technique of word-color interference" (2013) for more). This style reflects difficulties or relative ease in the transition from verbal to sensory-perceptual functions in a situation of cognitive conflict. The task includes 3 blocks, each containing 80 trials (20 trials per each of the four types of stimuli). In the first and second blocks, the speed of verbal and sensory-perceptual information processing is tested, respectively. The third block tests the speed of overcoming the interference effect (also known as the Stroop effect), i.e. the speed of changing the way of information processing from verbal to sensory-perceptual. Based on the total time to complete each block two indices are computed - interference index (see Formula 2) and verbality index (see Formula 3):

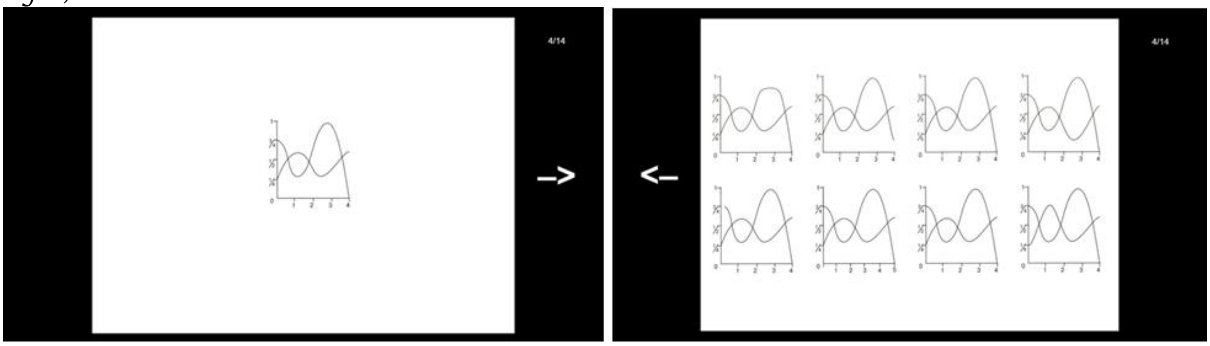
$$Interference\ Index = T_3 - T_2 \quad (2),$$

$$Verbality\ Index = \frac{T_2}{T_1} \quad (3),$$

where T_i is the amount of time of completion of block i. The values of the verbality index close to 1 indicate that both ways of information processing are equally preferred, while values lower/higher than 1 indicate preferences towards sensory-perceptual/verbal ways of information processing, respectively. As for the interference index, lower values indicate relative ease of overcoming the interference effect (i.e. more flexible cognitive control), while higher values indicate difficulties in this process (i.e. more rigid cognitive control).

Reflectivity - impulsivity style was assessed with the Matching Familiar Figures Test (MFFT) developed by J. Kagan and adapted by S. F. Sergeev. In the test, participants are provided with a sample image and a number of similar images. The goal of the task is to find an image that is exactly the same as a sample image among a set of similar images. The training block includes 2 trials with a set of 6 similar images for each trial, and the main block includes 12 different trials with sets of 8 similar images. Switching between the sample image and the set of similar images is done by clicking on an arrow on the screen (see Figure 4). Two indicators are recorded during the task: mean latency of the first response, and total number of errors. In general, more reflective people tend to spend more time on the task and do fewer total errors, whereas, impulsive individuals vice versa, tend to make more errors and spend less time on the task in total.

Figure 4. Example of the item in the Matching Familiar Figures Test (MFFT). Left: the sample image. Right: the set of 8 images in the MFFT that look similar to the sample image, but only one of them fully matches the sample image. Clicking on the arrow switches from the left screen to the right, or vice versa.



All tests were programmed with PsychoPy (version 2021.1.4) (Peirce et al., 2019), converted into psychojs (version 2020.2), and uploaded to Pavlovia, a platform for online experiments. Tests were presented in the following order: Stroop task, Gottschaldt Figures Test, Matching Familiar Figures Test. Preliminary pilot study on 6 participants was conducted to minimize possible technical problems in various web browsers and platforms. The full code of the experiment may be found on the Gitlab platform (see "CogStyles" for the link).

Procedure

Participants were asked to fill in the Google Form with general information about themselves and their game experience in LoL: nickname in LoL, region of their server, in-game rank in the 2020 season, experience of playing LoL (in years), gender, age, and contact information. Then, participants were sent their unique IDs, an instruction, and a link to the experiment. In the instruction, participants were asked to remove all distractors, sit comfortably, connect a computer mouse, and set convenient screen brightness. After completing the tests, the subjects reported this, after which it was checked whether the file with the participant's answers was saved.

As a motivation to participate in this study, it was told that after the data analysis participants would be provided with personal feedback on their cognitive styles and preliminary results of the study. Feedback included descriptions of cognitive styles, values of tests indicators, and their results relative to other participants (i.e. percentile). All of the questions on the feedback and the study itself were clarified by the researcher.

Data Analysis

Descriptive statistics are provided for all independent variables, i.e., minimum, maximum, mean, and standard deviation. Next step is to check all independent variables for multicollinearity with Spearman correlation and to remove all highly correlated independent variables. The variable with the highest variance inflation factor (VIF) is removed if necessary.

The dependent variable is the in-game rank, and the independent variables are interference index, verbality index, errors and mean time for the first answer in the MMFT, number of correct answers, and total time in the GFT. Additionally, we controlled for age, in-game experience in years, and number of looks at the sample in the MFFT. After fitting the linear model, heteroscedasticity is checked with the Breusch-Pagan test. And finally, the residuals of the model are tested for normality with the Shapiro-Wilk test. The same steps of analysis are performed then with experience operationalized as the total number of ranked matches during the current and the previous seasons. This part of data was extracted with the LoL API. All computations are performed with R and Python.

Results

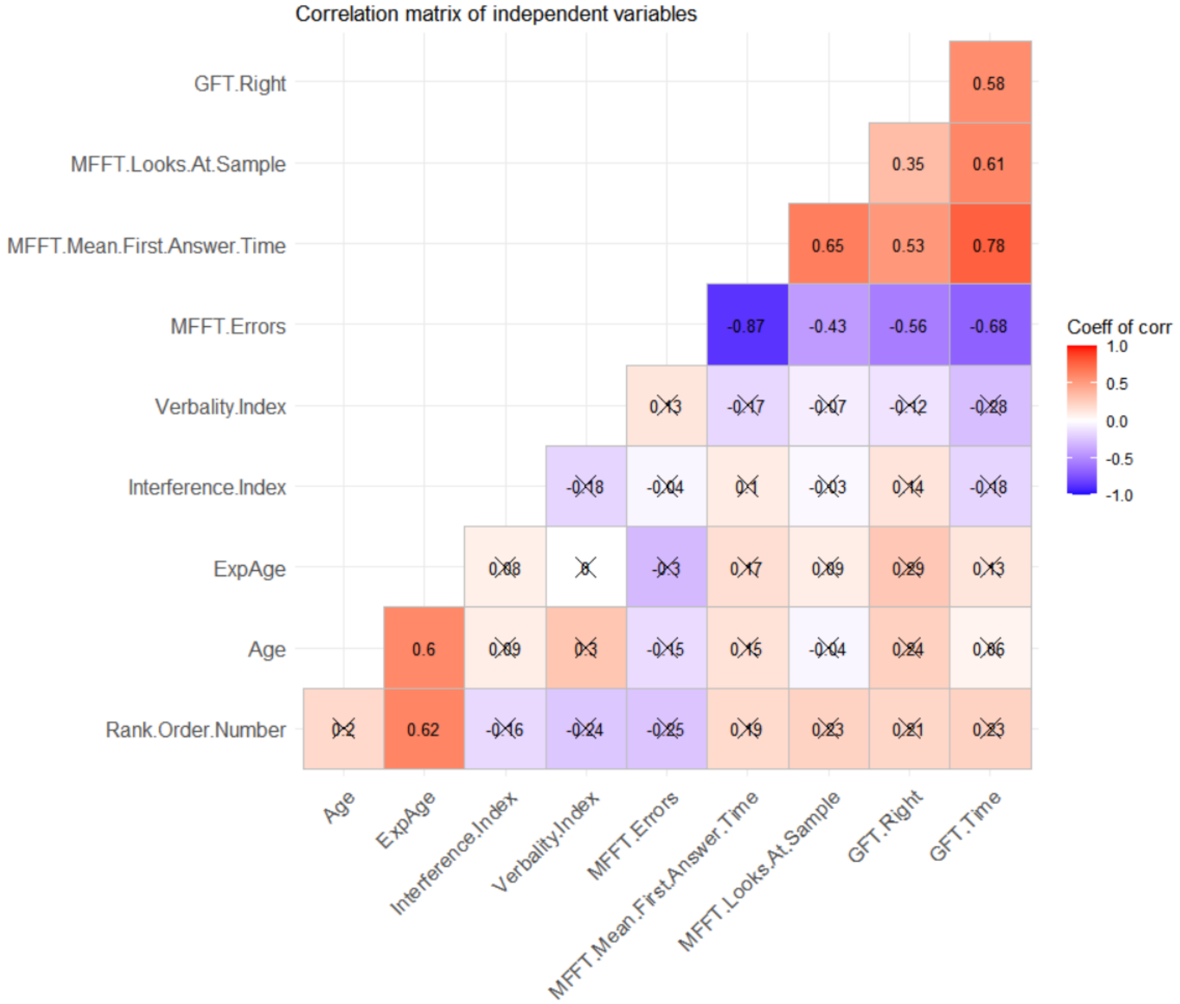
Descriptive statistics for the sample for independent variables are provided in Table 1. Experience in the number of matches is estimated for 34 people since the LoL API could not extract information on the 7 people before the season 2021, probably due to the changed nicknames.

Table 1. Descriptive statistics for independent variables (N=41, for experience in the number of matches N=34)

Variable	M	sd	min	max
Age	22.41	3.29	18	29
Experience (in years)	4.94	3.51	0	11
Experience (in number of matches played during two seasons)	597.10	683.16	4	2591
Interference Index (Stroop)	31.30	15.19	3.47	69.38
Verbality Index (Stroop)	0.99	0.08	0.85	1.21
Total time (GFT) (in seconds)	376.88	277.36	55.15	1480.93
Number of correct answers (GFT)	17.27	6.79	5.0	29.0
Mean time of 1st response (MFFT) (in seconds)	49.94	34.96	3.15	132.02
Number of errors (MFFT)	18.90	14.33	0.0	47.0
Mean number of looks at sample (MFFT)	5.20	3.56	1.0	17.75

Figure 5 shows the correlation matrix for all independent variables with crossed statistically insignificant correlations ($p > .05$). In-game rank moderately correlates with game experience in years ($r = .62$) only. The results of the GFT and the MFFT are also highly correlated with each other. For instance, time spent at the GFT positively correlated with the mean first answer time for the MFFT ($r = .78$). Likewise, the number of errors at the MFFT negatively correlated with the number of correct answers in the GFT ($r = -.56$). Both interference and verbality indexes did not significantly correlate with any of the independent variables.

Figure 5. Correlation matrix for all independent variables (N=41, ExpAge = game experience in years) (correlations with p < 0.05 crossed)



Correlations higher than 0.8 (Berry & Feldman, 1985) with variance inflation factor (VIF) greater than 5 (Kutner, Nachtsheim, Neter, & Li, 2005) were considered a threat to multicollinearity in this study which was only achieved between number of errors and the mean first time answer on the MFFT (r = -.87). VIF for the number of errors was 4.60, while for the mean first answer time it was 5.71. Thus, we removed the mean first answer time from further analysis.

Then, linear regression parameters were estimated with a resampling method called Jackknife. Specifically, we used 'leave-one-out' estimation, where only one data point is removed for each iteration. Jackknife approach was shown to be reliable for the small samples with the simulated data (Gavilanes, 2020). Table 2 shows parameters estimated with the jackknife approach, while Table 3 shows linear model parameters estimated on the full sample. The only statistically significant predictor was the game experience measured in years (p = .0002), while none of the test indicators reached the significance level of .05. Adjusted R^2 for the full sample model is .41 meaning that it can explain 41% of the total variance. According to the Shapiro-Wilk test, the distribution of the residuals does not significantly differ from normal (W = 0.97, p = .23). In addition, heteroscedasticity was not revealed with the Breusch-Pagan test (BP = 7.59, df = 8, p = .48). Thus, all assumptions of linear models are satisfied in this study.

Table 2. Linear model parameters estimated with the jackknife approach (with 1 data point removed on each iteration) (with experience in years)

Variable	β	bias	se	*t*	p	95% CI
(Intercept)	27.32	1.12	11.11	2.46	.02*	[4.87; 49.77]
Age	-0.22	0.01	0.40	-0.57	.58	[-1.03; 0.58]
ExpAge	1.19	-0.01	0.29	4.13	.0002***	[0.61; 1.77]
Verbality Index	-13.29	-0.77	12.49	-1.06	.29	[-38.53; 11.95]
Interference Index	-0.07	0.0	0.04	-1.57	.12	[-0.15; 0.02]
MFFT Errors	0.05	-0.1	0.10	0.53	.60	[-0.15; 0.26]
MFFT Looks At Sample	0.09	0.03	0.25	0.35	.73	[-0.42; 0. 60]
GFT Time	0.006	-0.002	0.005	1.39	.17	[0; 0.02]
GFT Right	-0.08	0.003	0.12	-0.63	.53	[-0.32; 0.17]

Note. .p < .1, *p < .05, **p < .01, ***p< .001. Bias is the difference between the parameters estimated on the full sample and estimation with jackknife approach.

Table 3. Linear model parameters estimated on the full sample (with experience in years)

Variable	β	se	*t*	p	Multiple R^2	Adjusted ΔR^2
Model (F(8, 32) = 4.41, p = .001**)					.52	.41
(Intercept)	28.44	10.62	2.68	.01*		
Age	-0.21	0.30	-0.70	.49		
ExpAge	1.18	0.28	4.25	.0002***		
Verbality Index	-14.06	9.85	-1.43	.16		
Interference Index	-0.07	0.05	-1.30	.20		
MFFT Errors	0.04	0.07	0.59	.56		
MFFT Looks At Sample	0.12	0.26	0.45	.66		
GFT Time	0.004	0.004	1.17	.25		
GFT Right	-0.07	0.14	-0.51	.61		

Note. .p < .1, *p < .05, **p < .01, ***p< .001

Alternative analysis for our data supposed that the in-game experience could be operationalized as a number of matches played during the two previous seasons. Since the initial rank in the beginning of the season depends on the rank from the previous season, we decided to use the total number of ranked matches during two seasons as an approximation of the in-game experience. The experience in years and in number of matches moderately correlated (r = .65), although the number of matches consider only the matches for two seasons, which is equal to two years. Figure 6 provides the same correlation matrix as in Figure 5, but on the subsample of 34 participants and with experience in number of matches. The number of matches negatively correlates with the number of errors (r = -.52) and positively correlates with the mean first answer time (r = .40) in the MFFT, as well as the number of looks at the sample in the MFFT (r=.39), number of correct answers (r = .35) and total time (r=.41) in the GFT. Based on the VIF, the number of errors in the MFFT was removed (VIF=6.93) from further analysis. Linear regression parameters were again estimated with the same jackknife approach (see Tables 4 and 5). Only the in-game experience was shows to be significant predictor of the in-game rank (p = .0008), as was revealed with the previous approach. Adjusted R^2 for the full sample model is .39. The distribution of the residuals does not significantly differ from normal (W = 0.98, p = .89). Finally, heteroscedasticity was not revealed with the Breusch-Pagan test (BP = 4.91, df = 8, p = .77). Thus, all assumptions of linear models are satisfied.

Figure 6. Correlation matrix for all independent variables (N=41, NumMatches = experience in the number of matches during current and previous seasons).

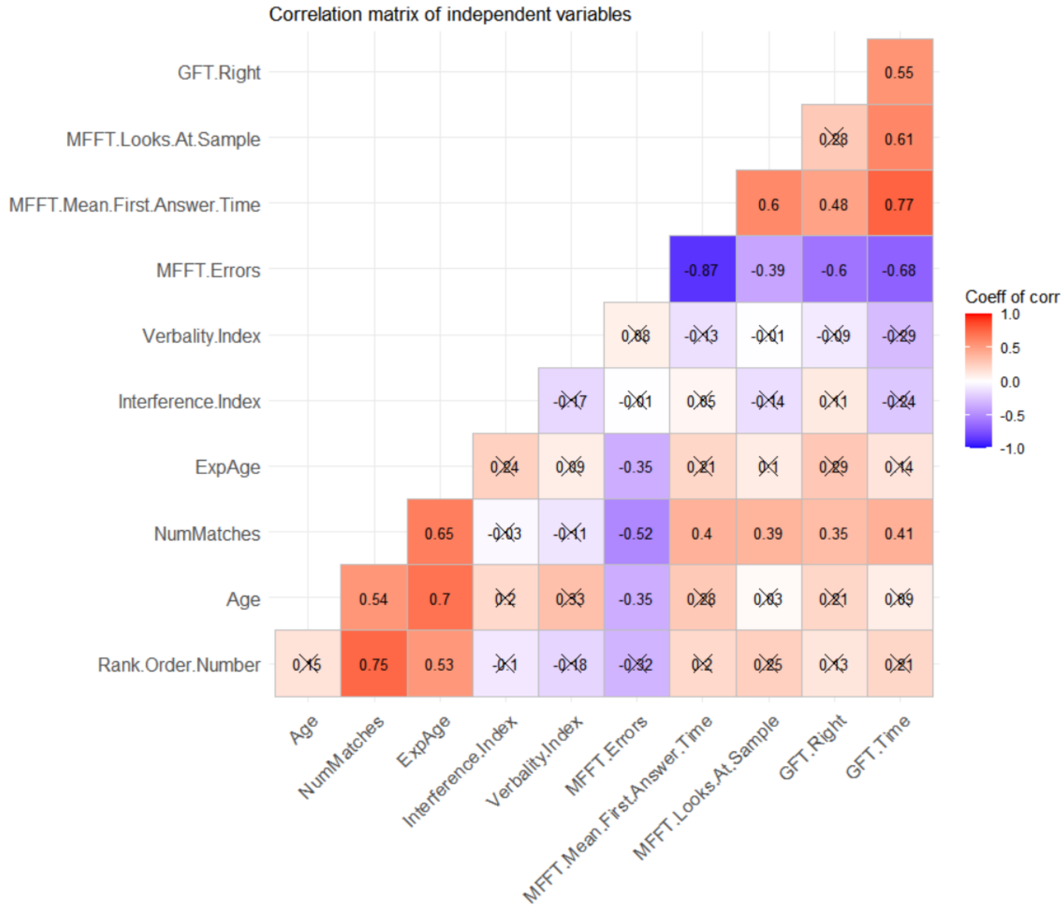


Table 4. Linear model parameters estimated on the subsample (N=34) with the jackknife approach (with 1 data point removed on each iteration) (with experience in number of ranked matches)

Variable	β	bias	se	*t*	p	95% CI
(Intercept)	24.10	-0.92	15.05	1.60	.12	[-6.52; 54.72]
Age	-0.77	0.20	0.51	-1.52	.14	[-1.79; 0.26]
NumMatches	0.01	0.0	0.0	3.66	.0008***	[0; 0.01]
Verbality Index	2.12	-2.91	17.06	0.12	.90	[-32.60; 36.83]
Interference Index	0.10	-0.01	0.07	1.49	.14	[-0.04; 0.25]
MFFT Looks At Sample	-0.03	-0.04	0.31	-0.09	.93	[-0.65; 0.60]
MFFT Mean First Answer Time	-0.01	-0.01	0.05	-0.15	.88	[-0.10; 0.09]
GFT Time	0.01	0.0	0.0	1.41	.17	[0; 0.01]
GFT Right	-0.17	0.02	0.17	-0.98	.33	[-0.52; 0.18]

Note. .p < .1, *p < .05, **p < .01, ***p< .001. Bias is the difference between the parameters estimated on the full sample and estimation with jackknife approach.

Table 5. Linear model parameters estimated on the full subsample (N=34) (with experience in number of ranked matches)

Variable	β	se	*t*	p	Multiple R^2	Adjusted ΔR^2
Model (F(8, 25) = 3.6, p = .007**)					.54	.39
(Intercept)	23.18	12.31	1.88	.07.		
Age	-0.56	0.38	-1.48	.15		
NumMatches	0.01	0.0	4.34	.0002***		
Verbality Index	-0.79	12.21	-0.07	.95		
Interference Index	0.10	0.07	1.46	.16		
MFFT Looks At Sample	-0.07	0.29	-0.25	.81		
MFFT Mean First Answer Time	-0.02	0.03	-0.53	.60		
GFT Time	0.01	0.0	1.38	.18		
GFT Right	-0.15	0.14	-1.05	.30		

Note. .p < .1, *p < .05, **p < .01, ***p< .001

Discussion

This study aimed to explore the link between different cognitive styles and players' performance in LoL. Specifically, it was hypothesized that players with higher in-game ranks demonstrate higher reflectivity, flexibility of cognitive control, and field-independence. None of the hypotheses was confirmed in our study. Although some correlations with the test indicators were found for the experience as the total number of ranked matches in the current and previous seasons, none of them was revealed to be a significant predictor of in-game rank. Notably, however, both operationalizations of in-game experience (in years and in the number of ranked matches) were found to be significant predictors of the in-game rank. Thus, the in-game experience, rather than specific cognitive styles, might be more important for the in-game rank.

The findings in this study are not fully consistent with the literature. In the previous studies, top LoL players demonstrated better results in the Stroop-switching test (Li et al., 2020) and a number of other tasks involving cognitive control (Large et al., 2019). In the current study cognitive control was assessed with the Stroop task, but using interference and verbality indexes. The reason of this difference in the results could be in the different structure of the used tasks and different measures. Also, cognitive control was interpreted in terms of cognitive styles, which was not done previously for esports players. Next, higher reflectivity was found in the results of Li and colleagues (2020) who demonstrated better impulsive control in top LoL players assessed with Go/No-Go Continuous Performance Test. Using MFFT, we did not find any impact of the reflectivity – impulsivity style on the in-game rank, probably due to the different used task. The absence of the significant results for each style could also be interpreted as that players in the ranked games are already more field-independent, reflective, and flexible than players in the normal games. This explanation goes in line with the previous study where it was shown that more active gamers demonstrate higher field-independence, flexibility of cognitive control, and reflectivity (Bogacheva & Voiskounsky, 2015). Nevertheless, 5 test indicators (three for the reflectivity - impulsivity style and two for the FD-FI style) weakly or moderately correlated with in-game experience measured as the number of ranked matches. Even though no causation could be inferred from the results of this study, one could assume that either with experience players become more reflective and probably more field-independent, or players with these styles are more likely to spend more time in LoL. Given the assumption that cognitive styles are consistent characteristics of information processing, the later explanation is more aligned with the theory. However, the insignificant regression results undermine correlation results.

It must be noted that the theory behind cognitive styles is not entirely reliable. Some of the problems were reviewed in the book by Zhang and Sternberg (2006). For instance, FD-FI and reflectivity - impulsivity styles were shown to be significantly related constructs, that is, people high on the reflective style also tend to be more field-independent. Another issue is that FD-FI is often criticized for not being style construct, but a perceptual ability. As to the reflectivity - impulsivity, the moderate correlations were found for MFFT task performance and intelligence tests, making this style related to the intelligence rather than separate cognitive style. Notably, we also find correlations between the test indicators for MFFT and GFT, which allows to assume that these tasks measure dependent concepts. Despite the serious theoretical issues, we find important that performance in these tasks still could be used for predictions, e.g., of educational attainment (Zhang, 2002; Kholodnaya, 2004; Riding & Caine, 1993; Sellah, Jacinta, & Helen, 2018, for reviews see Zhang & Sternberg, 2006). Moreover, previous study by Bogacheva and Voiskounsky (2015) allowed to hypothesize that there exists individual variability in performance on these tasks for gamers and non-gamers. Thus, the results of this study could be used by the theorists interested in revising the theory of cognitive styles and the nature of the constructs that are measured by the MFFT and GFT tasks.

This study has several other limitations. First, due to the specificity of the sample, fewer players participated in this study than was expected, which might affect the significance of our findings. Secondly, the distribution of the ranks in the sample was slightly skewed toward the players with the higher ranks. Thus, the following ideas for future research are proposed. First of all, a larger sample with participants from different servers could be collected. It would improve the significance of the results and allow to take into account cultural differences in cognitive styles and esports performance (see Kokkinakis and colleagues (2021) for examples of cultural differences in metagame in esports, e.g., the dominance of Korean metagame in LoL). One more idea is to investigate the effect of training in LoL on cognitive styles, which would allow checking the causality absent in this study. For instance, one such study used in-game data to understand the impact of training in a LoL summer camp and revealed improvement in team-focused aspects with no change in individualistic performance (Gerber, Sweeney, & Pasquini, 2019). The third idea is to check whether performance on the used cognitive tasks could be predicted by the in-game data. On the one hand, it would require a vast amount of both in-game and behavioral data. But on the other hand, it could help researchers in conducting large-scale cognitive studies with less effort and costs.

To the best of our knowledge, this study is the first that has assessed the predictive ability of cognitive styles in the context of esports performance. The results of the study suggest that cognitive styles are not effective parameters for such a selection, and in-game experience is more important. These results could possibly be considered in practice by esports managers when searching for a way to identify the most promising players. Also, this study contributes to the field of research on cognitive styles which are mainly used in the context of education and management nowadays.

Conclusion

Our results demonstrate that cognitive styles should not be used as predictors of a player's performance in LoL. The in-game experience measured in years and the number of ranked matches serve better predictors for the in-game rank.

Declarations of interest and funding

None declared. No specific funding for this research was received.

Data availability statement

Anonimized data, code for the analysis, and the code for the tasks could be found on the OSF repository (https://osf.io/y8r3j/).

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