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Normative Performance Profiles of College Aged Esport Athletes in a Pilot Study

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Abstract

Aims: This study aimed to holistically assess the physical and cognitive attributes of esports athletes.

Methods and Results: Forty-six adults between 18 and 32 years old with experience playing videogames were enrolled in this study. Participants completed assessments in five areas: demographics, self-report questionnaires, cognitive performance, physical performance, and gaming performance. Participants self-reported Overwatch ranking and physical activity participation (Pediatric Physical Activity Measure), and grip strength was measured with a handheld dynamometer. Seven domains of physical, mental, and social health and well-being were measured with the Patient Reported Outcomes Measurement Information System (PROMIS-29). The List Sorting Working Memory Test and Picture Sequence Memory Test from the National Institutes of Health (NIH) Toolbox Cognition Batteries were used to measure cognitive performance. Finally, esports performance was measured using a series of tasks through Alienware Academy and AIM Booster to record accuracy, reaction time, and targets hit. Participants were separated into high and low ranking groups for comparisons. This sample of esports athletes was similar to the general population for grip strength, each of the PROMIS-29 metrics, the List Sorting Working Memory Test, and the Picture Sequence Memory Test. Reaction time was the variable with the only significant difference between ranking groups.

Conclusion: This study represents a primary investigation of esports athletes using a holistic approach. By incorporating physical and cognitive components, the most important factors to esports athletes' health and performance can be better understood and applied.

Keywords: Overwatch, Esports, Competitive video gaming, video games, reaction time

Highlights

- High and low ranked Overwatch gamers scored similarly for physical, mental, and social health when compared to each other and to the general population.
- High rank gamers had significantly faster reaction times than low rank gamers.

- Task difficulty may be a significant differentiator of skill level and performance between competitive and recreational video game players.

Introduction

The cognitive and physiological metrics of competitive athletes in traditional sports have been extensively researched,⁽¹⁾ yet minimal information has been reported about the cognitive and physiological characteristics of esports athletes. In the past two decades, participation in esports has risen dramatically. By the end of 2020, nearly 2 billion people were aware of esports, with a total viewing audience of almost 500 million people.⁽²⁾ The rise of esports competitions and online gaming has proliferated in the sporting world, especially during the recent COVID-19 pandemic. Further information on the physiological, cognitive, and behavioral characteristics of esports athletes can aid current and future esports participants at amateur and professional levels.

Esports involve competitive video gaming whereby players combine into teams and compete against others in competitive arenas.⁽³⁾ Much like traditional sporting events, esports tournaments often have thousands of spectators. Some individuals are reluctant to characterize competitive video gaming as a sport because it involves less physical activity than traditional sports.⁽⁴⁾ However, researchers have suggested that competitive esports are indeed physically taxing, and excessive play can introduce overuse injuries to the hand, neck, and back.⁽⁵⁾ Performance may be impacted by the physical characteristics of the esports athlete,⁽⁶⁾ but these suggestions have yet to be quantified.

While there have been limited investigations into the physical attributes of esports athletes, many cognitive domains have been studied in gamers.^(7,8) A meta-analysis on the impact of action video games on cognition found that playing games improved cognition in the areas of perception, attention, spatial cognition, task-switching, inhibition, problem solving, and verbal cognition, though not all skills were improved equally and more research is needed to understand which skills are most important to gaming.⁽⁹⁾ Similar to traditional athletics, interpersonal skills are vital for performance in team settings. Although video gaming has often been thought of as a solitary activity, recent research shows that there are many social interactions between players as they attend large gaming tournaments and while playing together online.⁽¹⁰⁾ In competitive and recreational settings, video games are frequently played communally, with over half of teenagers' time spent playing with at least one friend.⁽¹¹⁾ Furthermore, 77% of the conversation is socioemotional in nature rather than task-oriented.⁽¹²⁾

Participation in esports requires gamers to be cognitively and socially astute as well as physically capable. In the rapidly growing esports enterprise, understanding the cognitive and physical characteristics is essential to understanding the best practices for esports athletes to lower injury risk while performing better. This information can also inform injury reduction efforts utilized by these teams and applied in other settings. The specific physiological and cognitive variables that impact esports performance are unclear. Therefore, the objective of this study was to conduct a holistic assessment of the physical and cognitive attributes of the esports athlete. To this end, the study aimed to describe the demographic and performance profiles of esports athletes as a foundation for exploring optimization of human performance in esports athletes.

Methodology

Participants

Using a cross-sectional study design, 46 adults between 18 and 32 years of age who had self-reported experience playing videogames were enrolled in the study. Individuals were recruited through a convenience sample on a university campus and were not excluded based on gender, race, ethnicity, or socioeconomic status. Individuals were included if they played video games (not exclusively *Overwatch*) recreationally or competitively, were able to provide written

informed consent, and were 18 years of age or older. Subject-candidates were excluded based on the following criteria: (1) non-English speaking or (2) having a physical impairment that did not allow them to complete testing.

. Individual performance was evaluated in five areas: demographics, self-report questionnaires, cognitive performance, physical performance, and gaming performance. A separate visual health and performance assessment was conducted and presented in another study. This study protocol complied with the Declaration of Helsinki and was reviewed and approved by The Ohio State University Institutional Review Board prior to subject recruitment.

Participant Characteristics

An electronic intake form was administered to collect demographic information such as name, date of birth, sex, race/ethnicity, handedness, education, and mother's education. This information was necessary to score the cognitive tasks, which are based on national datasets. The participants also self-reported their rank in Overwatch. High rank players were defined as those self-ranked diamond and above (skill ranking ≥ 3000 ; top ~20% of Overwatch players) while low rank players were defined as those self-ranked platinum and below (skill ranking < 3000 ; bottom ~80% of Overwatch players) or those without an Overwatch ranking.⁽¹³⁾ High rank players represented participants who played Overwatch more frequently or competitively, while low rank players represented a general population with occasional, general video game play.

The Patient Reported Outcomes Measurement Information System (PROMIS-29) is a self-reported instrument created by the United States National Institute of Health (NIH) which assesses seven domains of physical, mental, and social health and well-being.⁽¹⁴⁾ PROMIS-29 domains include physical function, anxiety, depression, fatigue, ability to participate in social roles and activities, pain interference, and pain intensity. By testing these domains in the U.S. general population and clinical groups, the NIH created a scaled scoring system so that PROMIS-29 survey results are scored on a normal t-distribution of the U.S. general population with a mean of 50 and standard deviation of 10.⁽¹⁴⁾ Fourteen item pools were tested in the U.S. general population and clinical groups using an online panel and clinic recruitment. For scale creation, a sub-sample was created reflecting demographics proportional to the 2000 U.S. census. The Pediatric Physical Activity Measure (PPAM) was also completed and is a self-reported questionnaire assessing exercise participation completed within the last week.⁽¹⁵⁾ The pediatric scale was utilized in lieu of a comparable adult measure in the PROMIS suite.

Grip strength was measured using a hand grip dynamometer (Jamar Plus+ Digital Hand Dynamometer; Sammons Preston, Bolingbrook, IL). The dynamometer was individually fit to each participant's hand, and the participants were seated, holding the device with 90° of elbow flexion. The test was completed three times for each hand with a minimum of 10 seconds of rest between each trial. The highest recorded measurement was used in data analysis.

Cognitive Performance

The List Sorting Working Memory Test is part of the NIH Toolbox Cognition Batteries and tests the participant's threshold for storing information in their working memory.^(16, 17) Participants are visually and audibly presented a series of items and are asked to verbally identify the objects in order based on certain size or classification criteria. The Picture Sequence Memory Test is also a part of the NIH Toolbox Cognition Batteries and is a test of the acquisition, storage, and retrieval of information provided in picture form. Participants were asked to replicate the

sequence order of several pictures depicting linked tasks. The protocols outlined by the NIH Toolbox were used throughout this portion of the study.

Gaming Performance

The participants were assessed using a single Alienware computer (Aurora R5 D23M; Dell Inc., Round Rock, TX), mouse (AW558; Dell Inc., Round Rock, TX), keyboard (AW768; Dell Inc., Round Rock, TX), and monitor (AW2518H; Dell Inc., Round Rock, TX). The monitor, desk, and chair heights were standardized (0.16m, 0.74m, and 0.44m, respectively), and the monitor was 0.35m from the front edge of the desk. The mouse and keyboard positions were adjusted to each participant's preferred location. For the Alienware Academy and the AIM Booster Tasks, in-game settings (i.e., mouse sensitivity, zoom sensitivity, key binds, display) were standardized for all participants. The Alienware Academy beta game suite was utilized to assess participants' reaction time within a game-setting at three difficulty levels. A blue and red figure appeared at different distances and the participant was instructed to only shoot the red figure, and the next set of figures appeared when the crosshair was returned to a central target. The participants completed each level with the instruction to complete the task "as fast as you can", and they were allowed one practice trial at the easiest of three levels. As the difficulty level increased, targets would appear in varied locations with increased speeds and varied distances.

The freeware beta AimBooster online software (aimbooster.com) was utilized to create a compilation of five custom designed tasks to measure participants' speed and accuracy in target-clicking tasks. Prior to the test, the participants were read scripted instructions (Table 1), and the task was demonstrated once. Each task was completed twice in succession, and the data from the second trial was recorded.

Table 1: Aim Booster Task Descriptions

Task ^a	Instructions
Challenge 1	In this game, you will click on targets as fast as you can. You have 3 minutes to click as many targets as possible. If the target goes away, this means you lose a life. If you lose 3 lives, the game will end early. Be as accurate as you when clicking on the target.
Precision	In this game, you will click on targets as fast as you can in 30 seconds as accurately as possible.
Target Click	In this game, you will need to click on as many targets as possible in 30 seconds. You will not lose lives in this game, but we will be tracking accuracy or how many times you miss.
Hover	In this game, you will hover over as many targets as you can without clicking in 30 seconds.
Sniping	In this game, you will need to click on targets as fast as you can in 30 seconds. Don't worry if you miss a target, just keep trying.
Challenge 2	In this game, you will click on targets as fast as you can. You have 3 minutes to click as many targets as possible. If the target goes away, this means you lose a life. If you lose 3 lives, the game will end early. Be as accurate as you when clicking on the target.

^aTasks are listed in the order performed.

Data Processing

Data summaries and analysis were conducted using R in RStudio.(18,19) Given the characteristics of the participants, race/ethnicity was categorized as non-Hispanic white, Asian, other, and not reported. Education was categorized into eight groups: high school graduate, some college credit but less than 1 year, one year of college at a 4-year program, no degree, two years of college at a 4-year program, no degree, three years or more of college at a 4-year program, no degree, Associates degree (e.g., AA, AS), Bachelor's degree (e.g., BA, AB, BS), and Master's degree (e.g., MA, MS, MEng, MEd, MSW, MBA).

Statistical Analysis

T-tests, assuming unequal variances, were used to compare the high and low rank mean scores for continuous variables of interest including the pediatric physical activities measures, cognitive performance, grip strength, Alienware Academy, and AimBooster tasks. Fishers' exact test was used for categorical variables for the physical activity variables. P-values are presented at the nominal level with a significance level of 0.05.

Results

Of the 46 participants in this study, 13 were classified as high rank and 33 as low rank. The mean age of the group was 20.9 (SD = 2.44) years. Table 2 presents the demographic characteristics of the study participants. The participants in the sample were mostly non-Hispanic white (69.6%), male (89.1%), right-handed (93.5%) and had at least some college education (91.3%) (Table 2). There were no significant differences in the demographics between the high and low rank groups. Means and standard deviation for the total sample, high and low rank for PROMIS-29, cognitive performance, physical activity, grip strength, and gaming performance are presented in Tables 3-6.

Table 2: Baseline demographic characteristics

	Total Sample (n=46)
Age, m(sd)	20.87 (2.44)
Sex, n (%)	
Female	5 (10.87)
Male	41 (89.13)
Race/Ethnicity, n (%)	
Non-Hispanic White	32 (69.57)
Asian	8 (17.39)
Other	4 (8.7)
No Response	2 (4.35)
Handedness, n (%)	
Left	3 (6.52)
Right	43 (93.48)
Education, n (%)	
High School Graduate	4 (8.7)
Some college credit but less than 1 year	4 (8.7)
One year of college at a 4-year program, no degree	3 (6.52)
Two years of college at a 4-year program, no degree	13 (28.26)
Three years or more of college at a 4-year program, no degree	14 (30.43)
Associates degree (e.g., AA, AS)	2 (4.35)
Bachelor's degree (e.g., BA, AB, BS)	4 (8.7)
Master's degree (e.g., MA, MS, MEng, MEd, MSW, MBA)	2 (4.35)
Rank, n (%)	
High	13 (28.26)
Low	33 (71.74)

Discussion

This research represents initial efforts to create a holistic profile of esports athletes. By considering the health, cognition, and physiological performance of competitive and recreational esports athletes and contextualizing this information with their respective gaming performance, this research provides a foundation for exploration of the multiple facets of healthful gaming. Notably, these findings provide insight into multiple domains of esports athletes and begin the development of profiles that use performance metrics to inform training and athlete selection in this growing population.

Physical Characteristics

Nearly 50% of professional and high level esports athletes participate in at least one hour of physical training each day.(5,20) Only one individual in our sample participated in vigorous physical activity for six to seven days each week; however, 15.56% of our sample reported participating in at least 10 minutes of physical activity for six to seven days each week. In a small sample of collegiate esports athletes (n=14), the participants performed nearly four hours of exercise each week,(21) which surpasses the current physical activity recommendations of the American College of Sports Medicine.(22) Although the majority of our sample represents amateur players, this contrast indicates possible inconsistencies in the physical activity patterns of esports athletes, and the potential differences between athletes at different skill levels.

A similar predictor of physical health, grip strength has also been shown to be representative of overall muscle strength.(23) The grip strength of participants in the present study was equitable to average grip strength levels reported for 20 year old males (82.5lbs - 91.3lbs) and females (62.5lbs).(24,25) Grip strength was not different between high and low ranked groups. Researchers have previously reported that hand dexterity (measured via pointing task and tapping speed) was predicted by grip strength (Table 3),(26) suggesting that research should further explore the relationship between grip strength and esports specific performance outcomes.

Self-Report Measures

Our findings (Table 3) indicate that esports athletes are similar to the general population on measures of physical function, anxiety, depression, fatigue, sleep disturbance, and the ability to participate socially. The findings from the PROMIS-29 are consistent for gamers of different skill levels. Previously, general physical fitness has been linked with improved cognitive performance and mental health.(27) Furthermore, physical fitness has been linked to faster single-plane eye-hand coordination task performance,(28) which is essential for esports athletes. Anxiety and depression have been associated with Internet Gaming Disorder and other psychological issues in gamers,(29,30) but our sample's anxiety and depression scores did not differ significantly from the general population. In competitive esports athletes, participation in a collegiate tournament was experienced as a stressful event that introduced moderate cognitive fatigue.(21) The ability to maintain performance while experiencing fatigue may be a determinant of skill level, but there was not a significant difference in the reported fatigue of the high and low rank participants. Intensity and duration of video game playing have been adversely associated with sleep quality and mental health in young adults.(31,32) In contrast, our sample scored similarly to the general population for sleep disturbance. The largest deviation from the general population mean for our sample was regarding the ability to participate socially (mean = 56.67, SD = 7.1) indicating that our sample self-reported a greater ability than the general population to fill their required social roles. However, this deviation was

still within one standard deviation of the general population mean and should not be considered atypical.

Table 3: Patient Reported Outcomes Measurement Information System (PROMIS-29), memory, and grip strength tests

	Total Mean(sd)	Low Rank Mean(sd)	High Rank Mean(sd)	Mean Difference (95% CI)	p-value ^a
PROMIS-29^b					
Physical Function	54.92 (3.95)	54.37 (4.31)	56.29 (2.55)	-1.93(-4.03, 0.18)	0.07
Anxiety	52.62 (8.23)	52.09 (7.88)	53.91 (9.25)	-1.81(-7.91, 4.28)	0.54
Depression	49.78 (9.37)	50.25 (8.82)	48.62 (10.88)	1.63(-5.48, 8.75)	0.64
Fatigue	48.53 (8.04)	49.69 (8.28)	45.68 (6.87)	4(-0.93, 8.94)	0.11
Sleep Disturbance	49.84 (7.36)	49.8 (7.72)	49.95 (6.7)	-0.14(-4.89, 4.6)	0.95
Ability to Participate Socially	56.67 (7.1)	57.17 (7.15)	55.43 (7.1)	1.74(-3.11, 6.59)	0.47
Memory					
List Sorting Working Memory Test Age ^c	107.47 (12.67)	107.94 (13.06)	106.31 (12.07)	1.63(-6.76, 10.02)	0.69
Picture Sequence Memory Test ^c	108.43 (15.67)	110.58 (14.56)	103 (17.63)	7.58(-3.96, 19.11)	0.19
Grip Strength					
Right hand	86.06 (20.73)	85.63 (22.17)	87.17 (17.31)	-1.54(-14.16, 11.07)	0.8
Left hand	83.31 (19.89)	82.31 (21.47)	85.84 (15.65)	-3.53(-15.23, 8.17)	0.54

^a Unpaired t-test assuming unequal variances

^b PROMIS-29 t-score

^c Age corrected standard score

Cognitive Performance

Previous research has disagreed upon the connection between esports performance and assessments of cognitive performance. In one study, professional action video gamers had enhanced visual spatial memory and working memory compared to amateur gamers.(7) However, other studies failed to find a correlation between video game playing and overall cognitive ability.(33,34) The results of the List Sorting and Picture Sequence memory tests for our sample (Table 3) were comparable to that of a healthy population when scored on an age-corrected standard scale (mean = 100, SD = 15).(14) On the Picture Sequence Memory Test, the low rank gamers (mean = 110.58, SD = 14.56) performed equally (p = 0.19) with the high rank gamers (mean = 103, SD = 17.63). Our data did not support the existence of a connection between esports ability and cognitive performance.

Gaming Performance

Previous research suggests that elite esports athletes have both higher accuracy and faster reaction times than the rest of the population.(35) Similarly, reaction time was significantly better for the high rank esports athletes in this study. In the Alienware Academy reaction time test, higher rank players had significantly better reaction times than lower rank players on the hardest difficulty (p = 0.05) (Table 4). This study supports previous research indicating that reaction time is an indicator of esports ability. Greater task difficulty appears to be a better method for eliciting skill related performance differences. The easier tasks may not have been

difficult enough to distinguish high versus low ranked participants because the tasks potentially did not require as much esports-specific skill to successfully complete. During gameplay, the level of difficulty is determined by the skill of the opponent, who are usually of similar rank. Therefore, improving reaction time could allow an esports athlete to out-perform their peers and increase the athlete's rank. The importance of reaction time was also supported by the results of the Aim Booster test's precision task (Table 5). High ranked gamers had similar accuracy to the lower ranked gamers, but on average reacted over 100 milliseconds faster. Although this difference was not statistically significant, in dynamic and competitive esports games like Overwatch, the first player to shoot in a one-on-one encounter has a distinct advantage, and the success of the other player depends heavily on the speed of their reaction.

Table 4: Alienware Academy average round reaction time

Level	Total Mean(sd)	Low Rank Mean(sd)	High Rank Mean(sd)	Mean Difference (95% CI)	p-value ^a
Easy	487.61	498.33 (115.67)	460.38 (105.51)	37.95(-35.36, 111.25)	0.3
Medium	457.39	469.09 (84)	427.69 (81)	41.4(-14.08, 96.88)	0.14
Hard	519.67	537.67 (102.93)	474 (91.39)	63.67(-0.3, 127.64)	0.05

^a Unpaired t-test assuming unequal variances [Insert Table 5]

Table 5: Aim Booster Tasks

	Total Mean(sd)	Low Rank Mean(sd)	High Rank Mean(sd)	Mean Difference (95% CI)	p-value ^a
Challenge 1					
Total Time (s)	34.4 (9.18)	34.74 (9.88)	33.45 (7.17)	1.29(-4.48, 7.06)	0.65
Accuracy (%)	92.34 (4.99)	92.14 (5.58)	92.84 (3.13)	-0.7(-3.33, 1.94)	0.6
Targets Hit	67.17 (23.92)	67.03 (24.97)	67.54 (21.96)	-0.51(-15.92, 14.91)	0.95
Final Targets/s	2.72 (0.46)	2.73 (0.45)	2.69 (0.48)	0.03(-0.29, 0.36)	0.82
Precision					
Targets Hit	6.52 (3.51)	6.67 (3.44)	6.15 (3.78)	0.51(-2.01, 3.03)	0.68
Accuracy (%)	34.27 (18.41)	35.05 (18.1)	32.28 (19.8)	2.77(-10.42, 15.96)	0.67
Avg. Reaction Time (ms)	734.66 (127.02)	766.18 (71.37)	654.64 (193)	111.54(-6.89, 229.98)	0.06
Target Click					
Click Hits	71 (9.98)	70.73 (10.38)	71.69 (9.26)	-0.97(-7.44, 5.51)	0.76
Target Click Accuracy (%)	95.6 (3.88)	95.78 (4.21)	95.16 (2.98)	0.62(-1.64, 2.87)	0.58
Hover					
Hits	61.61 (4.45)	61.42 (4.7)	62.08 (3.88)	-0.65(-3.43, 2.13)	0.63
Accuracy (%)	99.78 (0.58)	99.8 (0.54)	99.72 (0.7)	0.09(-0.36, 0.54)	0.69
Avg. Reaction Time (ms)	467.81 (36.74)	469.78 (39.2)	462.82 (30.42)	6.95(-15.27, 29.17)	0.53
Sniping					
Targets Hit	17.04 (4.45)	17.58 (4.86)	15.69 (2.9)	1.88(-0.48, 4.25)	0.12
Targets Total	24.8 (1.49)	24.82 (1.57)	24.77 (1.3)	0.05(-0.88, 0.98)	0.91
Accuracy (%)	38.17 (15.21)	38.64 (16.23)	36.96 (12.78)	1.68(-7.61, 10.96)	0.71
Challenge 2					
Total Time	45.17 (8.84)	45.6 (9.49)	44.1 (7.31)	1.5(-4.71, 7.71)	0.62
Accuracy (%)	92.63 (4.13)	93.06 (3.96)	91.54 (4.53)	1.52(-1.47, 4.51)	0.3
Targets Hit	90.3 (27.1)	90.55 (28.76)	89.69 (23.39)	0.85(-15.96, 17.67)	0.92
Final Targets/s	3 (0.37)	2.97 (0.39)	3.08 (0.28)	-0.11(-0.32, 0.1)	0.31

^a Unpaired t-test assuming unequal variances

Table 6: Pediatric Physical Activity Measure

	Total n=46 n(%)	Low Rank n=33 n(%)	High Rank n=13 n(%)	p-value ^a
How many days did you play sports for 10 minutes or more?				
No Days	21(45.65)	16(48.48)	5(38.46)	0.98
1 day	6(13.04)	3(9.09)	3(23.08)	
2-3 days	14(30.43)	10(30.3)	4(30.77)	
4-5 days	4(8.7)	3(9.09)	1(7.69)	
6-7 days	1(2.17)	1(3.03)	0(0)	
How many days were you so physically active that you sweated?				
No Days	4(8.7)	3(9.09)	1(7.69)	0.97
1 day	9(19.57)	7(21.21)	2(15.38)	
2-3 days	24(52.17)	17(51.52)	7(53.85)	
4-5 days	8(17.39)	6(18.18)	2(15.38)	
6-7 days	1(2.17)	0(0)	1(7.69)	
How many days did you exercise or play so hard that your body got tired?				
No Days	10(21.74)	7(21.21)	3(23.08)	0.9
1 day	16(34.78)	13(39.39)	3(23.08)	
2-3 days	14(30.43)	10(30.3)	4(30.77)	
4-5 days	5(10.87)	3(9.09)	2(15.38)	
6-7 days	1(2.17)	0(0)	1(7.69)	
How many days did you exercise or play so hard that your muscles burned?				
No Days	19(41.3)	13(39.39)	6(46.15)	0.69
1 day	12(26.09)	11(33.33)	1(7.69)	
2-3 days	8(17.39)	5(15.15)	3(23.08)	
4-5 days	6(13.04)	4(12.12)	2(15.38)	
6-7 days	1(2.17)	0(0)	1(7.69)	
How many days did you exercise or play so hard that you felt tired?				
No Days	7(15.22)	4(12.12)	3(23.08)	0.89
1 day	17(36.96)	13(39.39)	4(30.77)	
2-3 days	14(30.43)	11(33.33)	3(23.08)	
4-5 days	7(15.22)	5(15.15)	2(15.38)	
6-7 days	1(2.17)	0(0)	1(7.69)	
On a usual day, how physically active were you?				
Not at all	1(2.17)	1(3.03)	0(0)	0.49
A little bit	15(32.61)	10(30.3)	5(38.46)	
Somewhat	23(50)	19(57.58)	4(30.77)	
Quite a bit	5(10.87)	3(9.09)	2(15.38)	

Very Much	2(4.35)	0(0)	2(15.38)	
How many days did you exercise really hard for 10 minutes or more?				
No Days	15(32.61)	11(33.33)	4(30.77)	0.93
1 day	15(32.61)	12(36.36)	3(23.08)	
2-3 days	9(19.57)	6(18.18)	3(23.08)	
4-5 days	6(13.04)	4(12.12)	2(15.38)	
6-7 days	1(2.17)	0(0)	1(7.69)	
How many days were you physically active for 10 minutes or more?^b				
No Days	4(8.89)	3(9.09)	1(8.33)	0.97
1 day	1(2.22)	1(3.03)	0(0)	
2-3 days	18(40)	11(33.33)	7(58.33)	
4-5 days	15(33.33)	12(36.36)	3(25)	
6-7 days	7(15.56)	6(18.18)	1(8.33)	
How many days did you run for 10 minutes or more?				
No Days	22(47.83)	15(45.45)	7(53.85)	0.69
1 day	11(23.91)	10(30.3)	1(7.69)	
2-3 days	10(21.74)	7(21.21)	3(23.08)	
4-5 days	2(4.35)	1(3.03)	1(7.69)	
6-7 days	1(2.17)	0(0)	1(7.69)	

^a P-value from Fisher's exact test comparing low and high ranks

^b Missing a response in the high rank

This study is a first step towards the creation a comprehensive profile of esports athletes, and as a new endeavor, there are limitations worth noting. First, participants self-reported their game rankings. Self-report variables are inherently biased, and future research should aim to create a ranking metric that is both objective and game agnostic. Secondly, the standardized computer set-up may have impacted the performance of the participants who were accustomed to their own gaming configuration. Third, the small sample size may have limited statistical power. In addition, the small sample size forced the use of a binary system of high and low rank as opposed to a gradient system with three or more groups of varying skill. Next, the participants in this study were a heterogenous group with varied levels of experience potentially decreasing the ability to draw strong conclusions from the data. Finally, defining performance as a measurable quantity was difficult for this population. More precise and consistent metrics should be developed with future research.

In conclusion, this study provided insights into the profile of a recreational esports athlete and future studies should explore the physical and cognitive profile of professional esports athletes. With the growth of esports, it is essential to develop a comprehensive understanding of the world's newest professional athletes. Before being able to improve performance or mitigate adverse mental and physical health outcomes, researchers need to understand the characteristics of professional and recreational esports athletes.

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Declaration of interest statement

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References

1. Hernández-Mendo A, Reigal RE, López-Walle JM, Serpa S, Samdal O, Morales-Sánchez V, et al. Physical Activity, Sports Practice, and Cognitive Functioning: The Current Research Status. *Front Psychol* [Internet]. 2019 Dec 6 [cited 2021 Jan 11];10. Available from: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6908518/>
2. Adgate B. Esports Is Filling The Programming Void [Internet]. *Forbes*. 2020 [cited 2020 Dec 7]. Available from: <https://www.forbes.com/sites/bradadgate/2020/04/21/esports-is-filling-the-programming-void/>
3. Hamari J, Sjöblom M. What is eSports and why do people watch it? *Internet Res*. 2017;
4. Jenny SE, Manning RD, Keiper MC, Olrich TW. Virtual(ly) Athletes: Where eSports Fit Within the Definition of “Sport.” *Quest* 00336297. 2017 Jan;69(1):1–18.
5. DiFrancisco-Donoghue J, Balentine J, Schmidt G, Zwibel H. Managing the health of the eSport athlete: an integrated health management model. *BMJ Open Sport — Exerc Med* [Internet]. 2019 Jan 10 [cited 2020 Dec 7];5(1). Available from: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC6350739/>
6. Witkowski E. On the Digital Playing Field: How We “Do Sport” With Networked Computer Games. *Games Cult*. 2012 Sep 1;7(5):349–74.
7. Benoit JJ, Roudaia E, Johnson T, Love T, Faubert J. The neuropsychological profile of professional action video game players. *PeerJ*. 2020;8:e10211.
8. Toth AJ, Ramsbottom N, Kowal M, Campbell MJ. Converging Evidence Supporting the Cognitive Link between Exercise and Esport Performance: A Dual Systematic Review. *Brain Sci*. 2020 Nov 15;10(11).
9. Bediou B, Adams DM, Mayer RE, Tipton E, Green CS, Bavelier D. Meta-analysis of action video game impact on perceptual, attentional, and cognitive skills. *Psychol Bull*. 2018;144(1):77–110.
10. Seo Y, Jung S-U. Beyond solitary play in computer games: The social practices of eSports. *J Consum Cult*. 2016 Nov 1;16(3):635–55.
11. Lenhart A, Smith A, Anderson M, Duggan M, Perrin A. Teens, Technology & Friendships [Internet]. *Pew Research Center*; 2015 [cited 2020 Dec 7]. Available from: <https://www.pewresearch.org/internet/2015/08/06/chapter-3-video-games-are-key-elements-in-friendships-for-many-boys/>
12. Peña J, Hancock JT. An Analysis of Socioemotional and Task Communication in Online Multiplayer Video Games. *Commun Res*. 2006 Feb 1;33(1):92–109.
13. Milella V. Overwatch Competitive Rank Distribution: PC and Console - Updated Monthly [Internet]. *Esports Tales*. 2019 [cited 2020 Dec 7]. Available from: <https://www.esportstales.com/overwatch/competitive-rank-distribution-pc-and-console>
14. Cella D, Riley W, Stone A, Rothrock N, Reeve B, Yount S, et al. The Patient-Reported Outcomes Measurement Information System (PROMIS) developed and tested its first wave of adult self-reported health outcome item banks: 2005–2008. *J Clin Epidemiol*. 2010 Nov;63(11):1179–94.

15. Tucker CA, Bevans KB, Teneralli RE, Smith AW, Bowles HR, Forrest CB. Self-reported pediatric measures of physical activity, sedentary behavior, and strength impact for PROMIS: conceptual framework. *Pediatr Phys Ther Off Publ Sect Pediatr Am Phys Ther Assoc.* 2014;26(4):376–84.
16. Tulsy DS, Carlozzi N, Chiaravalloti ND, Beaumont JL, Kisala PA, Mungas D, et al. NIH Toolbox Cognition Battery (NIHTB-CB): The List Sorting Test to Measure Working Memory. *J Int Neuropsychol Soc JINS.* 2014 Jul;20(6):599–610.
17. Dikmen SS, Bauer PJ, Weintraub S, Mungas D, Slotkin J, Beaumont JL, et al. Measuring Episodic Memory Across the Lifespan: NIH Toolbox Picture Sequence Memory Test. *J Int Neuropsychol Soc JINS.* 2014 Jul;20(6):611–9.
18. R Core Team. R: A Language and Environment for Statistical Computing [Internet]. Vienna, Austria: R Foundation for Statistical Computing; 2018. Available from: <https://www.R-project.org/>
19. RStudio Team. RStudio: Integrated Development for R [Internet]. Boston, MA: RStudio, Inc.; 2019. Available from: <http://www.rstudio.com/>
20. Kari T, Karhulahti V-M. Do E-Athletes Move?: A Study on Training and Physical Exercise in Elite E-Sports. *Int J Gaming Comput Mediat Simul.* 2016;
21. Andre T, Walsh S, Valladao S, Cox D. Physiological and Perceptual Response to a Live Collegiate Esports Tournament. *Int J Exerc Sci.* 2020 Sep 21;13(6):1418–29.
22. American College of Sports Medicine. ACSM's Guidelines for Exercise Testing and Prescription. 10th ed. Lippincott Williams & Wilkins; 2017. 481 p.
23. Wang Y-C, Bohannon RW, Li X, Sindhu B, Kapellusch J. Hand-Grip Strength: Normative Reference Values and Equations for Individuals 18 to 85 Years of Age Residing in the United States. *J Orthop Sports Phys Ther.* 2018 Sep;48(9):685–93.
24. Dodds RM, Syddall HE, Cooper R, Benzeval M, Deary IJ, Dennison EM, et al. Grip strength across the life course: normative data from twelve British studies. *PLoS One.* 2014;9(12):e113637.
25. El-gohary TM, Abd Elkader SM, Al-shenqiti AM, Ibrahim MI. Assessment of hand-grip and key-pinch strength at three arm positions among healthy college students: Dominant versus non-dominant hand. *J Taibah Univ Med Sci.* 2019 Nov 28;14(6):566–71.
26. Martin JA, Ramsay J, Hughes C, Peters DM, Edwards MG. Age and Grip Strength Predict Hand Dexterity in Adults. *PLoS ONE [Internet].* 2015 Feb 17 [cited 2020 Dec 2];10(2). Available from: <https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4331509/>
27. Biddle SJH, Asare M. Physical activity and mental health in children and adolescents: a review of reviews. *Br J Sports Med.* 2011 Sep;45(11):886–95.
28. Van Halewyck F, Lavrysen A, Levin O, Boisgontier MP, Elliott D, Helsen WF. Both age and physical activity level impact on eye-hand coordination. *Hum Mov Sci.* 2014 Aug;36:80–96.
29. González-Bueso V, Santamaría JJ, Fernández D, Merino L, Montero E, Ribas J. Association between Internet Gaming Disorder or Pathological Video-Game Use and

- Comorbid Psychopathology: A Comprehensive Review. *Int J Environ Res Public Health*. 2018 Apr 3;15(4).
30. Marino C, Canale N, Vieno A, Caselli G, Scacchi L, Spada MM. Social anxiety and Internet gaming disorder: The role of motives and metacognitions. *J Behav Addict*. 2020 Oct 12;9(3):617–28.
 31. Hale L, Guan S. Screen time and sleep among school-aged children and adolescents: a systematic literature review. *Sleep Med Rev*. 2015 Jun;21:50–8.
 32. Altintas E, Karaca Y, Hullaert T, Tassi P. Sleep quality and video game playing: Effect of intensity of video game playing and mental health. *Psychiatry Res*. 2019 Mar;273:487–92.
 33. Powers KL, Brooks PJ, Aldrich NJ, Palladino MA, Alfieri L. Effects of video-game play on information processing: a meta-analytic investigation. *Psychon Bull Rev*. 2013 Dec;20(6):1055–79.
 34. Kühn S, Gallinat J, Mascherek A. Effects of computer gaming on cognition, brain structure, and function: a critical reflection on existing literature. *Dialogues Clin Neurosci*. 2019 Sep;21(3):319–30.
 35. Toth AJ, Kowal M, Campbell MJ. The Color-Word Stroop Task Does Not Differentiate Cognitive Inhibition Ability Among Esports Gamers of Varying Expertise. *Front Psychol* [Internet]. 2019 [cited 2020 Dec 7];10. Available from: <https://www.frontiersin.org/articles/10.3389/fpsyg.2019.02852/full?report=reader>