Perceptual-motor Abilities Underlying Expertise in Esports

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Abstract

The current study aimed to investigate the perceptual-motor abilities of esports players using an expert/nonexpert paradigm. A total of 75 participants (age: 24.17 ± 4.24 y, sex: male = 64, female = 11) were subdivided in accordance to their expertise level (i.e. professional: $n = 25$, recreational: $n = 25$ and control: $n = 25$). The perceptual-motor abilities assessed were manual dexterity, the speed-accuracy trade-off and a variety of response times. Groupwise differences were examined using multivariate and univariate analyses of variance. A significant multivariate effect of expertise level on performance characteristics was identified ($p < .001$, $\eta_p^2 = .35$). Significant univariate effects were identified on the movement time ($p < .001$, $\eta_p^2 = .42$), two-choice response time ($p = .038$, $\eta_p^2 = .09$), congruent precue response time ($p = .010$, $\eta_p^2 = .12$) and incongruent precue response time ($p = .047$, $\eta_p^2 = .08$). Professional esports players were less susceptible to the speed-accuracy trade-off when compared with recreational esports players and a control group. Furthermore, professional esports players demonstrated faster two-choice response times and were better at using or ignoring information preceding a stimulus to inform subsequent action when compared with the control group. Collectively, some perceptual-motor abilities may underlie expertise in esports, yet their ability to distinguish between professional and recreational esports players is limited. Future research should include more domain-specific measures to fully capture the underlying characteristics of expert esports players.

Keywords

Electronic sports, expert performance, excellence, skilled performance, video games, gaming

Introduction

Electronic sports (esports) involve individuals or teams of players who compete in video game competitions through human-computer interaction (Pluss et al., 2019). The world's first esports contest was held in the early 1970s, where players competed against one another in Spacewar! for a one-year subscription to the Rolling Stones magazine (Baker, 2016). Nowadays, there is a population of over 100 million players worldwide, competing in tournaments with prize pools exceeding $25 million (USD) and reaching audiences of over 50 million online viewers (Novak, Bennett, Pluss, & Fransen, 2019). Despite the high participation rates, only a select few players compete at the highest level of competition. As a result, a significant amount of interest is directed towards understanding how expert esports players develop their domain-specific skills. Although there are different esports genres (e.g. first-person shooters and multiplayer online battle arenas), esports players typically control an in-game avatar in a virtual environment to eliminate opposing players or achieve an objective (Kowal, Toth, Exton, & Campbell, 2018). To achieve successful performance, esports players seemingly integrate a range of perceptual-cognitive and perceptual-motor skills to produce goal-directed movements in a fast-paced environment. For example, esports players identify and process visual information displayed on a digital screen (i.e., task-relevant information), and auditory information from the in-game environment and team communications, to execute coordinated movements using a mouse and keyboard, or a hand-held controller. Evidentially, it is likely that perceptual-motor abilities play an integral role in esports performance. However, due to the recent emergence of esports, no research has investigated which perceptual-motor abilities underlie expertise in esports.

Currently, a limited amount of video game research exists to guide investigations into expert performance in esports (Gong et al., 2016; Kowalczyk et al., 2018; Tanaka et al., 2013). Despite this, a significant amount of research in video games (no competitive aspect) has documented aspects of performance that may be useful for understanding expertise in esports. For example, Toril, Reales, and Ballesteros (2014) demonstrated that video game training has shown to improve reaction time, attention, memory, and global recognition in older adults. However, the application of video game research findings to esports is not straightforward as the benefits will depend on the type of video game being played and the amount of training completed (Granic, Lobel, & Engels, 2014; Stafford & Dewar, 2014). In addition, it has been suggested that fast reflexes, good manual dexterity, excellent hand-eye coordination, advanced game sense, and greater tactical and strategic judgement underpin esports performance (Hemphill, 2005; Rambusch, Jakobsson, & Pargman, 2007). While these studies suggest to perceptual-motor abilities that may be relevant to esports performance, no peer-reviewed articles exist to support the aforementioned suggestions.

Esports players must possess the ability to use perceptual information to inform subsequent motor actions, a characteristic commonly attributed to other experts in sport (Chamberlain & Coelho, 1993; Ripoll, Kerlirzin, Stein, & Reine, 1995; Travassos et al., 2013). Anecdotally, within esports, a computer monitor displays the environmental information and actions are guided by the asymmetrical coordination of a keyboard and mouse. To outperform opponents, esports players make rapid decisions based on the available information in time-constrained situations. Indeed, an essential aspect of esports performance is the ability to manipulate the appropriate sequence of keystrokes and accurately move and click the mouse to perform their intended action. As such, the context in which esports players perform (i.e., the use of computer monitors and mouse and keyboard inputs) offers researchers the opportunity to develop assessment tasks that closely mimic the constraints of competition (Pluss et al., 2019). Developing externally valid assessment tasks provides researchers with the ideal context to measure the factors that underlie expertise of the domain in question (Hadlow, Panchuk, Mann, Portus, & Abernethy, 2018; Williams & Ericsson, 2005). Therefore, the current study aimed to describe the perceptual-motor abilities of esports players with an expert/nonexpert paradigm. Following previous expertise research, it was hypothesised that professional esports players would outperform recreational esports players and a control group in a battery of perceptual-motor assessments (Mann, Williams, Ward, & Janelle, 2007; Williams & Ericsson, 2005).

Methods

Participants

Data were collected from 75 participants (age: 24.17 ± 4.24 y, sex: male = 64, female = 11). Participants were *a priori* classified into three expertise groups: (1) professional (age: 22.05 ± 3.18 y, sex: male = 25, female = 0), (2) recreational (age: 25.80 ± 4.93 y, sex: male = 21, female = 4), and (3) control (age: 24.69 ± 3.84 y, sex: male = 18, female = 7). All participants were from the Oceania region (Australasia, Melanesia, Micronesia and Polynesia). The professional group consisted of players that compete on a full-time basis (a minimum of 38 hours of scheduled training per week) and represent a professional esports team at the highest level of competition. The professional group comprised 15 multiplayer online battle arena players (League of Legends and Heroes of the Storm) and 10 first-person shooter players (Overwatch and PUBG). The recreational group consisted of players that participate in esports on a casual basis (range between 10-20 hours per week), where the primary purpose of participation is an activity of leisure with the intention to improve. The recreational group comprised 13 multiplayer online battle arena players (League of Legends and Heroes of the Storm) and 12 first-person shooter players (Overwatch and PUBG). The control group consisted of healthy participants with no experience in esports. Before the commencement of the study, all participants were informed of the aims and the requirements of the research. The Institutional Ethics Research Committee approved this study.

Experimental procedure

The present study followed a cross-sectional study design to examine perceptual-motor abilities according to expertise level in esports players. The multifactorial testing battery was completed in a standardized order: i) manual dexterity, ii) speed-accuracy trade-off and iii) response times. In line with previous work, the perceptual-motor assessments were based on capturing some of the abilities that might underpin esports performance (Granic et al., 2014; Hemphill, 2005; Rambusch et al., 2007; Stafford & Dewar, 2014). All assessments were conducted in a laboratory setting under standardized conditions. Group-wise differences were examined through multivariate and univariate analysis of variance.

Manual dexterity. Fine motor skills and hand-eye coordination were assessed using a grooved pegboard (Lafayette Instrument, Lafayette, Indiana, United States of America). All procedures of the task followed the guidelines in the manual. The apparatus was placed with the peg tray orientated above the pegboard. Participants received instructions on how to perform the task (i.e., insert the pegs, matching the groove of the peg with the groove of the hole, filling the rows in a given direction as quickly as possible without skipping any slots). When using the right hand, the participant was asked to work from left to right, and with the left hand, in the opposite direction. Participants performed the task with their dominant hand first, followed by the non-dominant hand. Hand dominance was based on a participants preferred writing hand, which was their response to the following question "which hand do you prefer to write with?" (Oldfield, 1971). The participant was advised that only one peg should be picked up at a time and that only one hand is to be used. If a peg was dropped, the examiner did not retrieve it; rather, one of the pegs correctly placed (usually, the first or second peg) is taken out and used again. Last, the examiner demonstrated one row before allowing the participant to begin. A practice trial was not given, and the participant continued until all pegs were placed or until a time limit of three minutes was reached. Timing began after cueing the participant to begin and was terminated when the participant released the last peg. Time (s) was recorded to the nearest second. The output measures from the task included total completion time (s), number of drops (*n*) and number of correctly placed pegs (*n*). These output measures were summated to provide a total score (AU) for both the dominant and non-dominant hand.

Speed-accuracy trade-off. The ability to switch rapidly between targets while minimizing movement errors was assessed using an adapted computer-based clicking task (Fitts, 1954), which was developed using Unity software (Unity, Version 2018.3, 2018). The task was displayed on a digital screen (16:9 aspect ratio) and performed with a Razer Naga wired mouse (Razer, San Diego, California, USA) set at a cursor resolution/speed of 800 dots per inch. Participants received standardized instructions on how to perform the task (i.e., click back and forth between the targets as quickly and accurately as possible for a total of 10 seconds for each trial). Before the commencement of the task, participants were allowed 10 minutes to familiarize themselves with the equipment and standardized mouse settings. Participants completed all trials in a randomized order. Fitts' law models the speed-accuracy trade-off as a relationship between movement accuracy and speed, resulting in an index of difficulty. To evaluate the speed-accuracy trade-off, eight different indices of difficulty were assessed (ID1A, ID1B, ID2A, ID2B, ID3A, ID3B, ID4A, ID4B). According to Fitts' Law, as the index of difficulty (ID) increases, a greater movement time for execution is

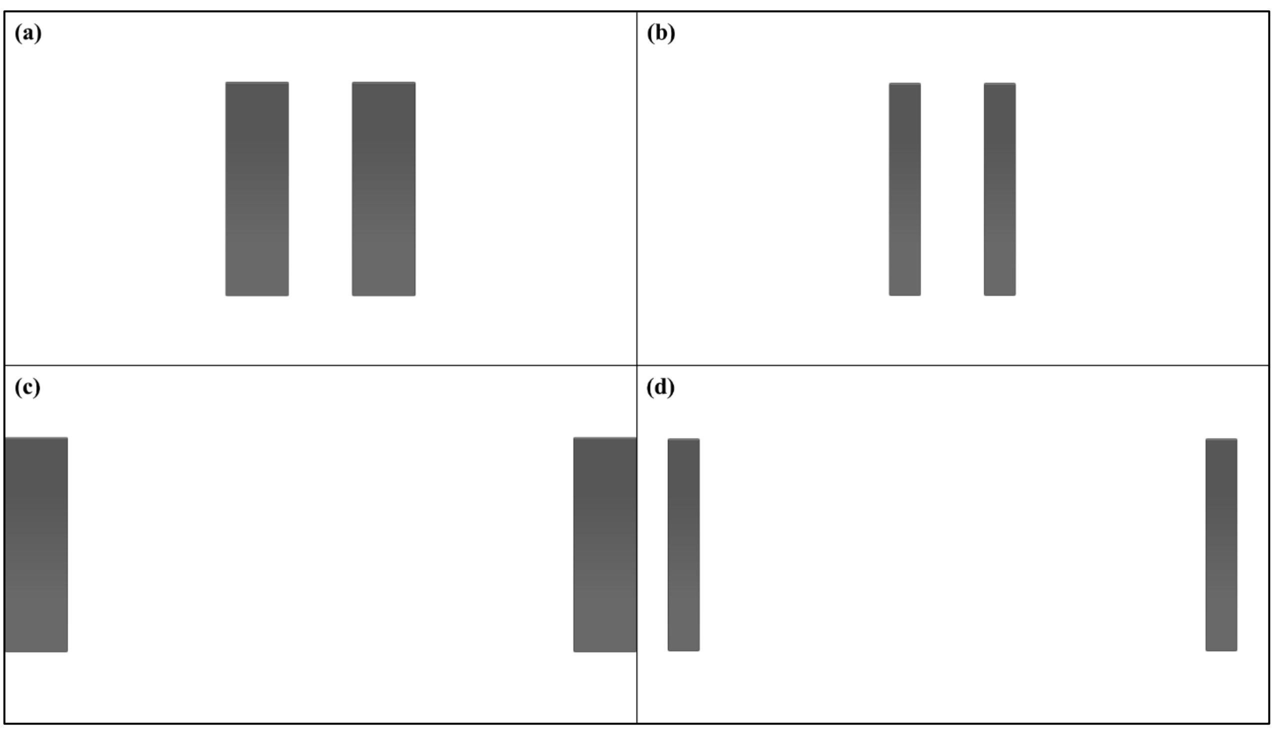

Figure 1. A visual depiction of different index of difficulties within the speed-accuracy trade-off task. Examples depicted are: ID1A (a), ID1B (b), ID4A (c), ID4B (d).

required, as movement time is as a function of the distance between the targets and the width of the targets. Therefore, in theory, the movement time will be greater across each of the eight different indices of difficulty, whereby the distance between the targets increases (e.g., ID 2 had a larger distance between the targets compared with ID 1). If an index of difficulty had a "B" option, the distance between the targets remained the same, however the width of the targets was half the size of the "A" option. A minimum of 90% accuracy was required for a successful trial. If 90% accuracy was not achieved, participants repeated the same trial until a successful trial was achieved. The accuracy of a trial was an automatic function developed within the software and was displayed at the end of each attempt. After a three-second countdown, the participant commenced a trial. After 10 seconds was reached, the trial was terminated by an automatic function within the software. The output measures from the task included accuracy (%: number of registered mouse clicks within the targets/number of total mouse clicks) and movement time (ms: total mouse clicks/average mouse clicks per second ×1000).

Response times. Simple two-choice and four-choice response times along with a go/no-go assessment that used congruent and incongruent precues in a four-choice response time task were assessed using a customized, four-button controller. All response time tasks were developed using Unity software (Unity, Version 2018.3, 2018). Participants received standardized instructions on how to perform the task (i.e., press the button that corresponds with the stimulus as quickly as possible). A three-second countdown was presented prior to the appearance of the stimulus for all tasks. After the blank circle/s appeared, one circle (stimulus) lit up yellow within a randomized period between two and four seconds. For example, one blank circle for simple response time, two blank circles for two-choice response time, etc. The precue consisted of a centralized small black dot appearing for 43 ms, 86 ms prior to the appearance of the stimulus in the same location (congruent) or a different location (incongruent) than the stimulus (Barela, Rocah, Novak, Fransen, & Figueiredo, 2019; Beavan et al., 2019). Participants were not made aware of the precue to ensure that it remained implicit, using implicit precues more accurately represents the direct manner of how esports players directly couple perception and action, without necessarily requiring explicit verbalisation (Adam et al., 1996; Barela et al., 2019; Michaels, 1988). Overall, there was a total of 24 trials for each of the tasks, and 12 trials for each condition for the precue task. Participants were allowed 10 minutes to familiarize themselves with the equipment. Participants completed all trials in a randomized order. For simple response time, participants responded with their index finger of their dominant hand. For two-choice response time, participants responded with their left-hand index finger for the left circle and the right index finger for the right circle. For four-choice response time and the precue task, participants responded with their left-hand middle finger for the outer left circle, left-hand index finger for the inner left circle, and vice versa. Across all tasks, participants were instructed to hover the respective finger/s in preparation for the stimulus, which limits the confounding effect of movement time (the time interval from the start of the movement and the end of the movement). The output measures from the task included response accuracy (%: correct or incorrect)—which was based on whether participants pressed the corresponding button to the stimulus circle—and response time (ms)—which represents the time between the appearance of the stimulus circle and the activation of a response button.

Data preparation. Participant's response times were analyzed according to their accuracy after data collection. For the response time tasks, responses that did not correspond with the stimulus circle were labeled as incorrect and the response time of that specific trial was omitted from the data. A total of 167 out of 7,200 (approximately

2%) of trials were labelled as incorrect. To highlight instances in which the participants missed the button or did not depress the button sufficiently to register a timely response, an outlier labeling rule was used. The labeling rule identified outliers when they were outside of the value associated with the values derived from multiplying each participant interquartile range (IQR) by 1.5, upon which values beyond the 25^{th} and 75^{th} percentiles ± 1.5 × IQR were considered outliers and discarded (Hoaglin & Iglewicz, 1987; Hoaglin, Iglewicz, & Tukey, 1986). A total of 53 out of 7,200 trials were labeled as outliers. This method has been previously applied in other studies assessing response time (Barela et al., 2019; Beavan et al., 2019).

Statistical analysis

Assumptions of normality were assessed using a Shapiro-Wilk test and visual inspection of the boxplots and histograms for all dependent variables. Descriptive statistics were calculated for all variables and presented as mean ± standard deviation. Preliminary analysis using a univariate analysis of variance was undertaken to determine the potential confounding effect of age. A multivariate analysis of variance (MANOVA) assessed the differences in means of the dependent variables (performance characteristics) between levels of the fixed factor (expertise level). Dependent variables included manual dexterity: dominant hand score (AU), non-dominant hand score (AU); speed-accuracy trade-off: accuracy (%), movement time (ms); response times: simple response time(s), two-choice response time(s), four-choice response time (s), congruent precue response time (s) and incongruent precue response time(s). The fixed factor was expertise level (professional, recreational, or control). Bonferroni *post-hoc* corrections were applied to allow for multiple comparisons and to determine individual differences between each paired level within the fixed factor. A criterion alpha level significance was set at $p < .05$. Partial Eta Squared effect sizes (η_p^2) were evaluated as small = 0.01, moderate = 0.06, and strong = 0.14 (Cohen, 2013). All statistical analyses were conducted using SPSS software (Version 25.0, IBM Corporation, United States of America).

Results

Table 1 displays the mean ± standard deviation for all data. A multivariate effect of expertise group on performance characteristics was identified ($p < .001$, $\eta_p^2 = .35$). For the manual dexterity assessment, there were no significant univariate effect of expertise level on the dominant hand and non-dominant hand score. For the speed-accuracy trade-off assessment, there was no significant univariate effect identified for accuracy. However, professional esports players demonstrated significantly faster movement times compared with recreational esports players and the control group ($p < .001$, $\eta_p^2 = .42$). For the response time assessments, there was no significant univariate effect identified for expertise group on simple or four-choice response time. However, professional esports players demonstrated significantly faster two-choice response times ($p = .038$, $\eta^2_p = 0.09$), faster congruent precue response times ($p = .010$, $\eta^2_p = 0.09$), and faster incongruent precue response times ($p = .047$, $\eta^2_p = .08$) compared with the control group, but not with recreational esports players.

Table 1. Perceptual-motor abilities of professional esports players, recreational esports players and control group.

	Group				
Performance characteristic	**Control (*n* = 25)**	**Recreational (*n* = 25)**	**Professional (*n* = 25)**	***F***	**η^2_p**
Manual dexterity					
Dominant hand (AU)	92.68 ± 12.51	88.08 ± 7.84	88.92 ± 7.93	1.60	0.04
Non-dominant hand (AU)	96.32 ± 14.26	94.52 ± 8.41	95.44 ± 7.51	0.18	0.01
Speed-accuracy trade-off					
Accuracy (%)	96.80 ± 2.21	96.86 ± 1.39	97.02 ± 1.42	0.11	0.00
Movement time (ms)	618.70 ± 67.40	523.51 ± 60.11	481.73 ± 76.19	26.48**	0.42
Response times					
Simple response time (ms)	313 ± 6.00	290 ± 5.01	296 ± 4.42	1.37	0.04
Two-choice response time (ms)	347 ± 5.03	325 ± 4.06	318 ± 3.21	3.43*	0.09
Four-choice response time (ms)	415 ± 6.24	394 ± 5.20	387 ± 3.84	1.95	0.05
Congruent response time (ms)	392 ± 6.44	356 ± 5.10	345 ± 4.90	4.92*	0.12
Incongruent response time (ms)	432 ± 5.44	410 ± 4.83	395 ± 5.15	3.19*	0.08

Note: * = *p* < .05, ** = *p* < .01.

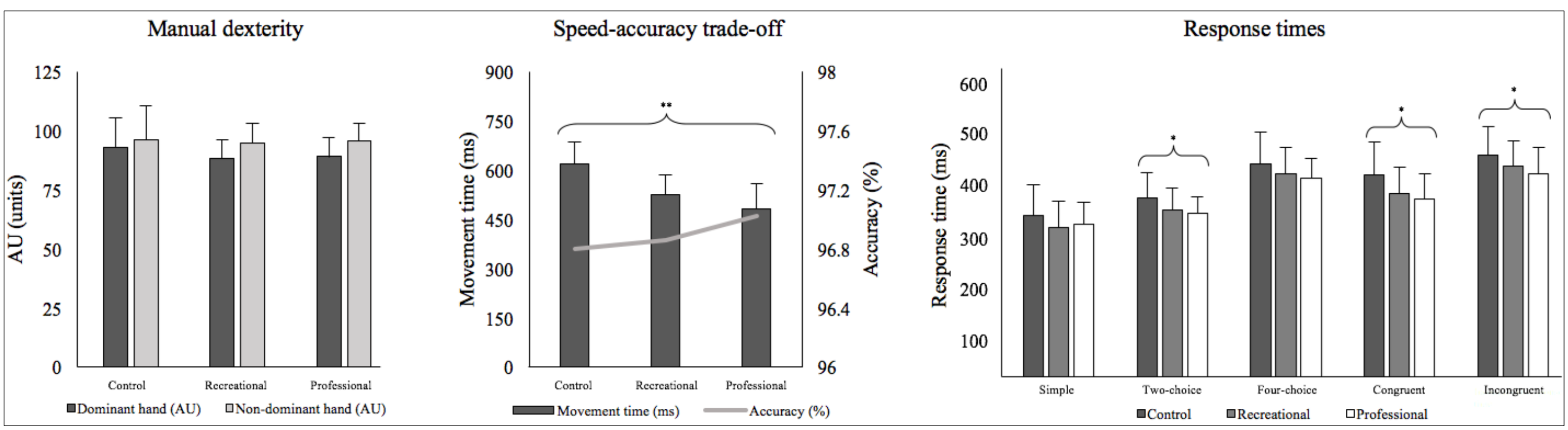

Figure 2. Perceptual-motor abilities of professional esports players, recreational esports players and control group (presented as mean ± standard deviation).

Note: ** = significant univariate effect between the professional group compared with the recreational and control group (*p* < .05), * = significant univariate effect between the professional group compared with the control group (*p* < .05).

Discussion

The current study examined the perceptual-motor abilities (e.g., manual dexterity, the speed-accuracy trade-off and a variety of response times) of three different *a priori* classified esports expertise levels (e.g., professional, recreational and control). Overall, some assessments of perceptual-motor abilities differentiated expertise level. Professional esports players were less susceptible to the speed-accuracy trade-off when compared with recreational esports players and a control group. Professional esports players also demonstrated faster two-choice response times and were better at using or ignoring precues to inform subsequent action when compared with the control group, but not with recreational esports players. Furthermore, manual dexterity in both the dominant and non-dominant hand, simple response time and four-choice response time was similar across all expertise groups.

The speed-accuracy task used in the present study required a minimum of 90% accuracy to be considered a successful trial. As a result, the primary emphasis in the task is on the accuracy of the movement rather than the speed of the movement. Professional esports players displayed quicker movement times when compared with recreational esports players and the control group. Furthermore, as the index of difficulty of the task increased, professional esports players were less susceptible to a speed-accuracy trade-off. Similarly, García, Sabido, Barbado, and Moreno (2013) reported expert handball players were better able to maintain their throwing accuracy despite an increase in throwing speed when compared with novice players. Furthermore, Beilock, Bertenthal, Hoerger, and Carr (2008) documented that expert golfers speed of movement had minimal effect on their putting accuracy while novice golfers demonstrated a significant decrease. Interestingly, the speed-accuracy trade-off task used in this study was an adaptation of the original tapping task, which originated as a predictive model of human movement (Fitts, 1954). As a result, the current task is considered to have high external validity to esports, given the representativeness of using a mouse for manual aiming on a computer screen. As such, it is not surprising that movement time in the speed-accuracy trade-off task discriminated between expertise levels, as several studies have highlighted the need for more domain-specific assessments in order to measure domain-specific expertise (Helsen & Starkes, 1999; Spitz, Put, Wagemans, Williams, & Helsen, 2018). Therefore, future research should further explore the relevance of the speed-accuracy trade-off in esports, in particular the time required to rapidly move to a target area as a function of the ratio between the distance to the target and the width of the target.

Despite no significant differences in the simple response time and four-choice response time, significant differences were identified in the two-choice response time and in a go/no-go assessment that used congruent and incongruent precues in a four-choice response time task. It is possible that esports players are more efficient at responding when presented with limited choices, but when adding more choices, they may not be better than the average population when responding in tasks with a generic stimulus. Overall, the results support the facilitating effect of congruent precues and the limiting effect of incongruent precues across all expertise groups (Barela et al., 2019; Beavan et al., 2019; Bugg & Diede, 2018; Chiew & Braver, 2016; Posner, 1980). When comparing the results of the precue task to the four-choice response time tasks, all participants were quicker with a congruent precue and slower with an incongruent precue than during a four-choice response time task where no precues were available. Evidentially, professional esports players are less likely to be affected by an incongruent precue (i.e., they are able to ignore irrelevant perceptual information) and respond quicker with a congruent precue (i.e., they are able to benefit from relevant perceptual information). This finding suggests that professional esports players may have a superior ability to process sources of visual information in more complex situations that require responses, where the sources of information are predictive of where a stimulus may appear. Indeed, this finding has practical relevance, as esports players need to continually interpret vast streams of perceptual (auditory and visual information) that appears on the screen while determining which information is relevant or irrelevant, often in an implicit (not easily verbalizable) rather than an explicit (easily verbalizable) manner. However, this study did not find differences between professional and recreational esports players which may suggest that the ability to use or ignore precue information may not necessarily be a sign of expertise but may be related to participation in esports at a general level.

Inherently, there are limitations present within the current study. First, standardized equipment (i.e., mouse) and settings (i.e., dots per inch) were employed. While this increases the control over the study design, it is possible that performing with a different mouse and sensitivity may require adaptation and will influence test performance. To minimise the influence this may have, participants received a familiarisation period to become accustomed to the equipment and settings and were encouraged to only proceed if they were comfortable to perform the task. Second, there is the possibility of order effects, which may include fatigue, practice, or other testing conditions (i.e., participants may gradually improve or decline due to factors in the testing environment). To minimize the influence this may have, participants were encouraged to proceed only if they were comfortable to perform the task. Third, the present study did not account for potential differences in experience, pre-existing abilities, or bidirectional effects between each group. As such, future research should consider the confounding influence this may have on test performance.

Conclusion

The current study aimed to investigate the perceptual-motor abilities of esports players with an expert/nonexpert paradigm. Professional esports players were less susceptible to the speed-accuracy trade-off compared with recreational esports players and a control group. Furthermore, professional esports players demonstrated faster two-choice response times and were better at using or ignoring precues to inform subsequent action compared with the control group, but not with recreational esports players. Collectively, some perceptual-motor abilities underlie expertise in esports.

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All authors listed made a substantial, direct, and intellectual contribution to the work, and approved it for publication.

Author's Declarations

The authors declare that there are no personal or financial conflicts of interest regarding the research in this article.

The authors declare that they conducted the research reported in this article in accordance with the Ethical Principles of the Journal of Expertise.

The authors declare that they are not able to make the dataset publicly available but are able to provide it upon request.

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