An investigation into the factors that underlie expertise in esports

by Matthew Anthony Pluss

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Certificate of Original Authorship

I, Matthew Pluss declare that this thesis, is submitted in fulfilment of the requirements for the award of PhD Thesis: Sport and Exercise Science, in the Faculty of Health at the University of Technology Sydney.

This thesis is wholly my own work unless otherwise referenced or acknowledged. In addition, I certify that all information sources and literature used are indicated in the thesis.

This document has not been submitted for qualifications at any other academic institution.

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Statement of Candidate Contribution

The valuable contribution of each author to the studies submitted as part of this thesis (Table I).

Table I. The contribution (%) of each author to study 1 to 2.

	Study 1						**Study 2**					
	Matthew Pluss	Kyle Bennett	Andrew Novak	Derek Panchuk	Aaron Coutts	Job Fransen	Matthew Pluss	Andrew Novak	Kyle Bennett	Derek Panchuk	Aaron Coutts	Job Fransen
Research design	70					30	50					50
Ethics application							80					20
Subject recruitment							100					
Data collection							100					
Data analysis							80					20
Statistical analysis												100
Manuscript preparation	100						100					
Manuscript revisions		10	10	10	10	50		10	10	10	10	50

Table I (cont'd). The contribution (%) of each author to study 3 and 4.

	Study 3						Study 4					
	Matthew Pluss	Andrew Novak	Kyle Bennett	Derek Panchuk	Aaron Coutts	Job Fransen	Matthew Pluss	Andrew Novak	Kyle Bennett	Derek Panchuk	Aaron Coutts	Job Fransen
Research design	50					50	50					50
Ethics application	80					20	80					20
Subject recruitment	100						100					
Data collection	100						100					
Data analysis	80					20	80					20
Statistical analysis						100		50				50
Manuscript preparation	100						100					
Manuscript revisions		10	10	10	10	50		10	10	10	10	50

Table I (cont'd). The contribution (%) of each author to study 5 and 6.

	Study 5						Study 6						
	Matthew Pluss	Andrew Novak	Kyle Bennett	Derek Panchuk	Aaron Coutts	Job Fransen	Matthew Pluss	Andrew Novak	Kyle Bennett	Ignatius McBride	Derek Panchuk	Aaron Coutts	Job Fransen
Research design	50					50	50						50
Ethics application	80					20	80						20
Subject recruitment	100						100						
Data collection	100						100						
Data analysis	80					20	80						20
Statistical analysis						100				50			50
Manuscript preparation	100						100						
Manuscript revisions		10	10	10	10	50		10	10		10	50	50

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List of Abbreviations

×	By
Δ	Change in
=	Equals
<	Less than
>	Greater than
%	Percentage
±	Plus-minus sign
cm	Centimetres
e.g.	For example
ES	Effect size
F	F statistic
h	Hours
ICC	Intraclass correlation coefficient
i.e.	That is
MANOVA	Multivariate analysis of variance
n	Number
p	P value
η^2_p	Partial eta squared effect size
RM-MANOVA	Repeated measure multivariate analysis of variance
s	Seconds
SD	Standard deviation
v	Versus
y	Year

Abstract

For many decades, researchers have explored the limits of human achievement in a variety of domains (e.g. music, science, sport, technology, and academia). Despite a plethora of research into how human expertise is achieved, several recurring complications persist when assessing the characteristics of an expert and studying the development of expertise. The first is the bias associated with using retrospective recall to examine an individual's developmental activities in the pursuit of excellence. Second, developing tasks that allow participants to accurately reproduce the behaviours observed in a performance environment in a laboratory setting remains difficult. Lastly, as the attainment of expertise often occurs over a long time span, there are factors (e.g. systematic training environments) that can confound the development of expertise. Despite providing insights into how expertise is attained, expanding on these findings in different domains may further improve our understanding about expertise. Therefore, the current thesis investigated the extent to which electronic sports (esports) may present an opportunity to add to the existing knowledge of expertise through six research studies.

Study 1 framed esports (competitive video gaming) as a contemporary window into human expertise that can address some of these limitations associated with current methodologies used in expertise research. Examining expertise through an esports lens has the following advantages: (i) developmental activities are objectively tracked and automatically logged online, thus limiting the reliance on retrospective recall when attempting to map participation histories, (ii) esports performance is conducted in a relatively controlled environment, which offers researchers a unique opportunity to conduct investigations that sufficiently represent real-world performance, and (iii) esports expertise has emerged with limited influence of guided systematic training environments (e.g. talent development programs and structured coaching). Therefore, Study 1 argues

that esports provides an opportunity to complement the current understanding about expertise.

Study 2 investigated the extent to which esports expertise can be detected using a battery of perceptual-motor assessments using an expert/nonexpert paradigm. Study 2 findings indicated that professional esports players were better able to maintain their accuracy whilst producing shorter movement times 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 congruent or incongruent information preceding a stimulus to inform subsequent action when compared with the control group.

Study 3 explored Fitts' law, a law that describes the relationship between movement speed and accuracy which governs the control of voluntary movement in humans, in manual aiming tasks using an expert/non-expert paradigm and a targeted subset of the data collected for Study 2. Overall, professional esports players produced shorter movement times and adapted their movement time to changes in task difficulty with imposed accuracy demands when compared with recreational esports players and a control group.

Study 4 investigated the test-retest reliability and construct validity of a commonly used and practically relevant esports perceptual-motor skill assessment (Mobalytics Proving Ground Test). In terms of the main performance characteristics, the esports group demonstrated superior performance in total score and mechanics compared with the control group, however background processing and map awareness did not distinguish between groups. When analysing the variables related to each aspect of the performance characteristics, most variables associated with mechanics and background processing significantly differed between groups. Overall, the esports perceptual-motor skill assessment used in the current study can to some extent distinguish between an esports player from a control group.

Study 5 examined the influence of the quantity of practice and the in-game performance during practice of professional esports players over an eight-week period immediately prior to a major esports tournament. Overall, the quantity of practice and in-game performance during practice explained a small proportion of the variance in tournament performance. More specifically, measures of in-game performance (i.e. kill/death ratio and score) were most associated with better tournament performance during practice, rather than the quantity of practice during the lead up to competition.

Study 6 examined the practice activities (i.e. time spent in-game and time spent in competition) of professional and semi-professional esports players over a 52-week period. Study 6 reported that professional esports players on average accumulate more practice over a one-year period than semi-professional players, of which a large part involves competitive play. While this finding may appear to be logical, it demonstrates that even at considerable levels of expertise, practice time appears to distinguish intermediate from expert performers.

Overall, the current thesis provided new insights into assessing the characteristics of experts and studying the development of expertise in a relatively new domain known as esports. In terms of assessing the characteristics of experts in esports, perceptual-motor abilities may underlie expertise in esports, yet their ability to distinguish between professional and recreational esports players is limited when assessments are not able to replicate the perception and action demands of competitive performance. Furthermore, computerised speed-accuracy trade-off tasks provide a task-representative measure of domain-specific expertise. However, esports perceptual-motor skills remain difficult to quantify and further research is needed to develop and assess the validity and reliability

of these representative assessments. Whereas when studying the development of expertise in esports, the quantity of practice had a limited acute association with better tournament performance in a homogeneous sample of expert esports players. However, over longer time scales, practice time appears to distinguish professional from semi-professional esports players.

Keywords: electronic sports, expert performance, excellence, skilled performance, video games, gaming

Chapter 1:

Introduction

Statement of the problem

Excellence (i.e. the quality of being outstanding or extremely good) in human endeavours and expert performance (i.e. expert skill or knowledge in a particular field) have received considerable interest from researchers and practitioners for several decades, across a wide variety of domains (Ericsson, 2014; Ericsson & Charness, 1994; Ericsson, Hoffman, & Kozbelt, 2018; Osborne, Simon, & Collins, 2003). For example, researchers have spent considerable time and effort to understand the uniqueness of expert performers like Beethoven and Mozart (Riessman, 2008). This same fascination with experts exists across many other domains, such as human creative endeavours, chess, medicine, academia, and sport, where experts are often revered for their exceptional skills (Ericsson, 1999; Ericsson & Smith, 1991; Ericsson, Whyte IV, & Ward, 2007; Williams & Ford, 2008). When researchers want to understand how expertise is attained, they often focus on two fundamental aspects: determining the characteristics that distinguish experts and understanding their developmental pathways (Ericsson, 2014; Ericsson et al., 2018; Ericsson & Smith, 1991; Janelle & Hillman, 2003). When attempting to capture the characteristics of an expert, researchers typically conduct group-wise comparisons of skilled and lesser skilled individuals in tasks that are designed to replicate a real-world environment within a controlled setting (Lens & Rand, 2000; Ryff, 1989; Ryff & Singer, 2008). However, capturing expertise is a challenging task given the inherently complex nature of performance in some domains (Pinder, Headrick, & Oudejans, 2015; Williams & Ericsson, 2005). For example, when attempting to understand expertise in Association football, researchers need to consider that expertise is multifactorial, given many factors (i.e. physical, technical, cognitive, etc.) contribute to performance (Bennett, Novak, Pluss, Coutts, & Fransen, 2020; Huijgen, Elferink-Gemser, Lemmink, & Visscher, 2014; Meylan, Cronin, Oliver, & Hughes, 2010; Williams & Reilly, 2000). Furthermore, as the proportion of a population who become experts is very small, and expertise generally develops over long time periods, predicting who will become an expert is nearly impossible. Ideal study designs would require following huge samples within the population for what could be more than a decade (Ericsson, Krampe, & Tesch-Römer, 1993; Mann, Dehghansai, & Baker, 2017; Phillips, Davids, Renshaw, & Portus, 2010; Wagner & Stanovich, 1996). Therefore, rather than using a longitudinal follow-up design, expertise researchers typically recruit highly skilled individuals and ask them to reflect on various factors that may have influenced their development of expertise throughout the many years, if not decades of their career (Baker, Cote, & Abernethy, 2003; Howard, 2012; Ward, Hodges, Starkes, & Williams, 2007). Although a plethora of research exists within expertise across a range of domains, there are several issues (e.g. subjective bias when using retrospective methods and the ability to develop ecologically valid tasks) that are inherently associated with assessing the characteristics of an expert and studying the development of expertise, which may limit our current understanding about expertise (Araújo, Cruz, & Almeida, 2007; Ericsson & Smith, 1991; Farrow, Reid, Buszard, & Kovalchik, 2018; Patel, Doku, & Tennakoon, 2003; Pinder et al., 2015).

As expert performance is maximised under conditions that more closely replicate performance in a real-world scenario (Farrow et al., 2018; Pinder et al., 2015). An issue when assessing the characteristics of an expert is that it is difficult to develop tasks that accurately describe and measure performance under specific task constraints that effectively capture the functional responses of performers in representative situations (Ericsson & Lehmann, 1996; Helsen & Starkes, 1999; Williams & Ericsson, 2005). Consequently, when developing representative tasks, researchers are often faced with a trade-off between higher degrees of experimental control (i.e. laboratory settings) for less replication of performance (i.e. field settings), or vice versa (Belling, Suss, & Ward, 2015; Berkowitz & Donnerstein, 1982; Brunswik, 1947, 1955, 1956; Causer, Barach, &

Williams, 2014; Dicks, Davids, & Button, 2009; Ericsson & Lehmann, 1996; Pinder, Davids, Renshaw, & Araújo, 2011; Travassos et al., 2013; Voss, Kramer, Basak, Prakash, & Roberts, 2010). As a result, many of the domain-specific assessments may indirectly measure a related function or ability rather than the specific and complex skills that underlie expert performance (Hadlow, Panchuk, Mann, Portus, & Abernethy, 2018; Williams & Ericsson, 2005). Although it is and will continue to be an ongoing issue to some extent, researchers are currently seeking alternative methods to explore valid and reliable ways to capture expert performance (Ericsson & Lehmann, 1996; Hadlow et al., 2018). Recent advancements in technology offer a range of tools for researchers to develop representative tasks that more readily represent the performance requirements of a task in situ (Ericsson & Smith, 2011; Hadlow et al., 2018; Williams & Ericsson, 2005). For example, researchers may develop a simulator task to assess an aviator's decision-making and flight control performance (Kennedy, Taylor, Reade, & Yesavage, 2010). The task itself can incorporate motion, vibration and sound elements that would be experienced during a real-world environment (Taylor, Kennedy, Noda, & Yesavage, 2007). Furthermore, a pilot's perspective of a real-world visual environment can be generated and displayed by a form of technology, whereby the aircrafts position and communication frequencies can be regularly updated (Taylor, O'Hara, Mumenthaler, Rosen, & Yesavage, 2005). This particular example highlights how effective a representative task design can be at capturing and replicating performance under specific task constraints, which can elicit the functional responses of performers in situations that represent performance.

Another issue when studying the development of expertise, is that researchers often rely on using retrospective methods to examine the learning history of an individual (Baker et al., 2003; Baker, Côté, & Abernethy, 2003; Baker, Hodges, & Wilson, 2018). The main consideration with using retrospective methods is the bias that undermines the validity and reliability of the data, given it is often shaped by the memory recall ability of an individual (Baker et al., 2018; Côté, Ericsson, & Law, 2005; Howard, 2011). Furthermore, the findings may be limited by the statistical analyses (i.e. analysis of variance procedures or simple univariate models of association) adopted by researchers (Baker & Farrow, 2015; Gauthier & Bukach, 2007; Paley, 2006). However, the attainment of expertise is not entirely linear and involves a more dynamic interaction between variables (Baker & Horton, 2004; Côté, Baker, & Abernethy, 2007; Phillips et al., 2010). Therefore, more advanced statistical techniques are required to identify the relationship between practice and expertise (Baker and Young, 2013). Consequently, longitudinal investigations are an alternative approach to overcome the limitations associated with using retrospective methods to examine the learning history of an individual (Côté et al., 2007; Ward et al., 2007). However, there are several difficulties (i.e. expensive, time consuming, and requires a sufficient sample size to account for poor participant retention) when conducting longitudinal investigations, which may explain the limited research that currently exists (Patel et al., 2003). As a result, expertise researchers are seeking alternative methods (i.e. quasi-longitudinal designs, tracking practice over a competitive season) to improve our understanding about the development of expertise (Abernethy, Thomas, & Thomas, 1993; Ward et al., 2007).

Prefix

Determining the characteristics of an expert and understanding the developmental pathway of an expert are two of the main objectives in expertise research (Ericsson, 2014; Ericsson et al., 2018; Ericsson & Smith, 1991; Janelle & Hillman, 2003). Recently, electronic sports (esports) appears to be a domain that has emerged and may offer new insights into assessing the characteristics of an expert and examining the development of expertise (Study 1). Esports involves individuals and/or teams of highly skilled players who compete in a form of organised video game competitions (Hamari & Sjöblom, 2017; Pluss et al., 2019; Wagner, 2006). Nowadays, researchers are interested in exploring the psychology of esports and the advantages that esports offers to researchers within the expertise field (Bányai, Griffiths, Király, & Demetrovics, 2019; Cottrell, McMillen, & Harris, 2019; Pedraza-Ramirez, Musculus, Raab, & Laborde, 2020; Pluss et al., 2019).

While 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). A significant amount of research in video games (no competitive aspect) has documented aspects of performance (e.g. fast reaction time, good manual dexterity, and excellent hand-eye coordination) and the requirements of becoming an expert (e.g. extensive practice) that may be useful for understanding expertise in esports (Hemphill, 2005; Rambusch, Jakobsson, & Pargman, 2007). Although these studies suggest which characteristics (e.g. domain-general abilities and domain-specific skills) and the requirements (e.g. learning history and practice activities) that may be relevant to expertise in esports, no peer-reviewed articles exist to support the aforementioned suggestions.

Study 2 provided insight into the domain-general abilities underpinning esports performance at various expertise levels (e.g. professional, recreational, and control).

Domain-general abilities may be foundational for the development of expertise but have limited ability to distinguish those with high levels of expertise from those with moderate levels of expertise. As a result, future research needed to further explore the speed-accuracy trade-off and a variety of response times in esports players and focus more on domain-specific measures.

Study 3 further explored Fitts' law with a computerised speed-accuracy trade-off task in esports players using an expert/nonexpert paradigm. As a computerised speed-accuracy trade-off task appeared to have value as an esports-specific performance measure as it discriminates between expertise level in esports players. Future research needed to utilise computer-based assessments to conduct domain-specific investigations to understand the characteristics of expert esports players.

Study 4 assessed the test-retest reliability and construct validity of a commonly used online esports perceptual-motor skill assessment using an expertise paradigm. Evidentially, while an esports perceptual-motor skill assessment is practically relevant and may appear to have sufficient face-validity for measuring domain-specific expertise in esports performance, it may not be necessarily useful for assessing the characteristics of esports players. Future research needed to develop more representative assessments of esports performance and move towards examining performance in-situ.

Study 5 examined the association between practice over an eight-week period immediately prior to a major esports tournament and performance on a competitive tournament. While practice quantity alone did not distinguish between performance levels in a homogeneous group of professional esports players. Whether the quantity of practice distinguishes between performance levels of professional esports players in comparison to lesser skilled esports players (e.g. semi professional and amateur) remained an area for future research.

Study 6 examined the quantity of practice of professional esports players and semi-professional esports players over a 52-week period. Professional esports players on average accumulate more practice over a one-year period than semi-professional players, of which a large part involves competitive play. Esports expertise is subject to similar positive relationships between practice and performance revealed in other domains of expertise and highlights that sufficient practice time may be an important contributor to the attainment of expertise.

Study objectives

The current thesis aimed to address some of the key issues in expertise research, with assessing the characteristics of an expert and studying the development of expertise. The first study focused on identifying and discussing the limitations of current methodologies aimed at investigating the factors that underlie expertise. This study also aimed to provide insights into how esports can expand our current understanding of expertise in human behaviour in general. Studies 2 and 3 explored the association between domain-general abilities of esports players and their expertise level (e.g. professional, recreational, and control). Collectively, Studies 2 and 3 investigated the extent to which these assessments can be used to assess esports-specific expertise. Following, Study 4 examined the reliability and validity of an esports-specific perceptual-motor skill assessment that is commonly used by esports players and coaches and is considered a practically-relevant assessment of esports performance. The final two studies explored the association between practice and expertise in professional and semi-professional esports players' performance. Initially, Study 5 examined the association between practice over an eight-week period immediately prior to a major esports tournament and performance on a competitive tournament. Next, Study 6 examined the practice activities of professional and semi-professional esports players over a longitudinal period to further strengthen the existing knowledge on the relationship between practice and performance within the context of expertise in esports. Collectively, the main objective of this thesis was to improve our understanding about the development and assessment of expertise within the motor domain, through an in-depth investigation of the factors underlying esports expertise.

Study 1: Esports: the chess of the 21st century (Chapter 3)

Aim: Study 1 aimed to argue why esports offers researchers an opportunity to better our understanding of expertise in human behaviour in the modern world.

Significance: Study 1 was the first theoretical paper to highlight the opportunities that esports offers researchers interested in understanding expertise in human behaviour. While a significant amount of research has been conducted on how expertise develops, and can be assessed, esports expertise research may address some of the complications associated within the study of expertise in other fields. Therefore, this study proposed a theoretical framework and practical recommendations to guide expertise research in esports.

Study 2: Perceptual-motor abilities underlying expertise in esports (Chapter 4)

Aim: Study 2 aimed to describe the perceptual-motor abilities of esports players using an expert/non-expert paradigm.

Hypotheses: It was hypothesised that professional esports players would outperform recreational esports players and a control group in a battery of perceptual-motor assessments.

Significance: Study 2 provided insight into the domain-general abilities underpinning esports performance at various expertise levels (e.g. professional, recreational, and control). Furthermore, Study 2 demonstrated that domain-general abilities may be foundational for the development of expertise but have limited ability to distinguish those with high levels of expertise from those with moderate levels of expertise.

Study 3: Exploring fitts' law: the speed-accuracy trade-off in esports (Chapter 5)

Aim: Study 3 aimed to explore Fitts' law with a computerised speed-accuracy trade-off task in esports players using an expert/nonexpert paradigm.

Hypotheses: It was hypothesised that professional esports players would display significantly shorter movement times when compared with recreational esports players and a control group in a speed-accuracy trade-off assessment. Furthermore, it was hypothesised that professional esports players will be better at adapting their movement time to changes in task difficulty with imposed accuracy demands when compared with recreational esports players and a control group.

Significance: Study 3 demonstrated that a computerised speed-accuracy trade-off task appears to have value as an esports-specific performance measure as it discriminates between expertise level in esports players. Furthermore, it highlighted the importance of using computer-based assessments to conduct domain-specific investigations to understand the characteristics of experts in esports.

Study 4: Assessing the reliability and validity of an esports perceptual-motor skill assessment (Chapter 6)

Aim: Study 4 aimed to assess the test-retest reliability and construct validity of a commonly used online esports perceptual-motor skill assessment using an expertise paradigm.

Hypotheses: Given the assessment is proposed as an assessment and training tool for esports players, it was hypothesised that there will be minimal differences between the results of successive measures of the same measure carried out under the same conditions (i.e., test-retest reliability). Regarding construct validity, it was hypothesised that esports players would demonstrate superior performance compared with the control group.

Significance: The findings from Study 4 demonstrated that even when an esports perceptual-motor skill assessment is practically relevant and may appear to have sufficient face-validity for measuring domain-specific expertise in esports performance, it may not be necessarily useful for assessing the characteristics of esports players.

Study 5: The relationship between the quantity of practice and in-game performance during practice with tournament performance in esports: An eight-week prospective study (Chapter 7)

Aim: Study 5 aimed to examine the association between practice over an eight-week period immediately prior to a major esports tournament and performance on a competitive tournament.

Hypotheses: It was hypothesised that the quantity of practice and in-game performance during practice in the weeks preceding a major competitive event will explain a proportion of the variance in tournament performance. Furthermore, it was hypothesised that more practice and better practice performance will be associated with better tournament performance.

Significance: Study 5 was the first to show the association between practice time and performance, and subsequent tournament performance in professional esports players. Furthermore, Study 5 highlighted that while deliberate and purposeful practice is undoubtedly necessary to reach a high level of expertise in esports, it is apparent that the quality of practice may be more useful to distinguish between performance levels in a homogeneous group of professional esports players.

Study 6: Examining the quantity of practice of professional and semi-professional esports players: A 52-week longitudinal study (Chapter 8)

Aim: Study 6 examined the quantity of practice of professional esports players and semi-professional esports players over a 52-week period.

Hypotheses: Based on the findings of the previous study, it was hypothesised the quantity of practice an esports player engages in would only be moderately associated with their current expertise level. Furthermore, it was hypothesised that professional esports players would accumulate more practice over a 52-week period when compared with semi-professional esports players.

Significance: Study 6 demonstrated that esports expertise is subject to similar positive relationships between practice and performance revealed in other domains of expertise and highlights that sufficient practice time may be an important contributor to the attainment of expertise.

Chapter 2:

Review of literature

Aim of the review

The evolving and dynamic nature of expertise has made it difficult for researchers to assess the characteristics of an expert and study the development of expertise over the last several decades. Overall, the primary aim of the literature review is to demonstrate what is known about expertise, how well our knowledge on expertise is established and where future research in expertise might be best directed. To begin with, the literature review provides an introduction and perspective into expertise and highlights the primary aims of expertise research, which involves assessing the characteristics of an expert and studying the development of expertise over the last several decades. Furthermore, this section goes into depth about the interest in expertise research, briefly mentions some of the common ways to investigate expertise and provides an in-depth analysis of the characteristics of an expert. Part 2 further details two of the most common methods employed by researchers to assess the characteristics of an expert, which include verbal protocols and the use of representative task designs. Part 3 describes the frequently used methods by researchers to study the development of expertise, which include retrospective recall and concurrent learning activities. Part 4 highlights certain factors that may influence the development of expertise, in particular is the access to guided systematic training environments and the importance of domain-specific practice. Part 5 summarises the main issues associated with current methodologies aimed at assessing the characteristics of an expert and studying the development of expertise and proposes implications for future expertise research. Lastly, Part 6 documents the rise of competitive video gaming and how a relatively new domain known as electronic sports (esports) has emerged recently, which can potentially offer new insights into assessing the characteristics of an expert and studying the development of expertise.

Part 1 – Introduction and perspective

People spend many years, or even decades of their life aiming to reach the highest level of performance (Ericsson, 2006; Ericsson et al., 1993; Ward et al., 2007; Ward, Hodges, & Williams, 2004). Some examples include becoming an Olympic gold medallist or a grandmaster in chess, both of which require considerable time investments (Ericsson et al., 1993). Initially, it was reported that a minimum of 10 years' experience is necessary to reach grandmaster in chess, a rank that has only been officially attained by approximately 2,000 players worldwide (Chase & Simon, 1973). Since this hypothesis, understanding the requirements to reach the highest level of performance has further been explored in music (Davidson, Moore, Sloboda, & Howe, 1998; Lehmann, 1997; Papageorgi et al., 2010; Waters, Underwood, & Findlay, 1997), sport (Baker & Horton, 2004; Baker, Horton, Robertson-Wilson, & Wall, 2003; Singer & Janelle, 1999; Starkes & Ericsson, 2003), medicine (Haynes, Devereaux, & Guyatt, 2002; Norman et al., 2018; Schmidt & Boshuizen, 1993; Schmidt & Rikers, 2007) and academia (Bell, 1997; Berliner, 1988, 1991; Manross & Templeton, 1997).

Expertise researchers have been particularly interested in how expertise develops, and why expertise can be attained by some, but not by others (Baker & Horton, 2004; Bruce, Farrow, & Raynor, 2013; Erickson, 2015). For many decades, the nature versus nurture debate has driven expertise research, with some arguing that the attainment of expertise is determined by the genetic makeup (i.e. nature), whereas others arguing that the environment (i.e. nurture) is central to expertise development (Horn & Masunaga, 2006). Despite the ongoing debate between nature versus nurture and the emergence of more integrated perspectives (e.g. The Developmental Model of Giftedness and Talent), it is generally accepted that the amount of practice is related to the attainment of expertise across many domains (Baker et al., 2003; Ericsson & Starkes, 2003; Gagné, 1995, 2013).

Overall, whether it be everyday tasks (e.g. reading or writing) or exceptional accomplishments (e.g. artists, athletes, and scholars), the two primary aims of researching expertise is to gain information about the characteristics of an expert and how an individual acquires a particular skillset over time (Gobet, 2015). Furthermore, researchers may research expertise in other domains to further improve our understanding about expertise in human behaviour. Recently, electronic sports (esports) appears to be a domain that has emerged and may offer new insights into assessing the characteristics of an expert and examining the development of expertise. Esports involves individuals and/or teams of highly skilled players who compete in a form of organised video game competitions (Hamari & Sjöblom, 2017; Pluss et al., 2019; Wagner, 2006). Nowadays, researchers are interested in exploring the advantages that esports offers to researchers within the expertise field (Bányai et al., 2019; Cottrell et al., 2019; Pedraza-Ramirez et al., 2020; Pluss et al., 2019).

What is an expert?

An expert refers to an exceptionally gifted individual that has acquired a specific skillset often over an extended period of time within their own specialised field (Weinstein, 1993). Furthermore, the characteristics displayed by experts are often what distinguishes them from lesser skilled individuals from the same domain (Ericsson & Lehmann, 1996). Although it depends on the complexity of the domain, expertise is more clearly evident in fields with quantifiable outcomes of performance (Carling, Reilly, & Williams, 2008). For example, the performance outcome of a chess match is either a win, loss, or draw for each individual player. From an expertise perspective, it is highly likely that a grandmaster chess player will be victorious in a chess match when competing against a lower ranked player (Ericsson, 2006). The ability for a grandmaster chess player to utilise the skills associated with their expertise to outperform a lesser skilled counterpart encapsulates the concept of expert performance. Another example in a more complex domain, where the performance is more difficult at quantifying is sport, where athletes integrate domain-general abilities and domain-specific skills to produce goal-directed movements in a fast-paced environment. Expert athletes display superior decision-making ability, which is reflected in reduced response times and greater response accuracy (Ripoll, Kerlirzin, Stein, & Reine, 1995; Vaeyens, Lenoir, Williams, Mazyn, & Philippaerts, 2007; Vaeyens, Lenoir, Williams, & Philippaerts, 2007). Also, experts demonstrate the ability to anticipate upcoming events, which is developed through extensive procedural and declarative knowledge (Savelsbergh, Williams, Kamp, & Ward, 2002). Lastly, experts identify and process task-relevant information more efficiently, which allows for appropriate direction of attention (Moran, Byrne, & McGlade, 2002). Overall, the ability for an expert athlete to utilise the skills associated with their expertise to outperform a novice athlete provides further context into what is an expert. Therefore, studying expert performance is an integral part of the study of human expertise.

Studying expertise

Ericsson and Smith (1991) initially proposed a framework to study expertise in human behaviour, often referred to as the expert performance approach. The expert performance approach is critically evaluated for its potential to be used as the guiding framework for understanding and assessing human expertise (Ericsson, 2003; Williams & Ericsson, 2005). The primary aims of the expert performance approach is to identify the key characteristics of an expert and understand how expertise is developed (Ericsson, 2003). According to the expert performance approach, assessing expertise in human behaviour has three distinct stages (Ericsson & Smith, 1991; Ericsson et al., 2007).

The first stage involves developing representative tasks that provide accurate and reproducible measurements of the performance characteristics relevant to the domain of interest that can be objectively evaluated in a laboratory-setting (e.g., video/film and virtual reality) and/or field setting (e.g., match analysis and simulations) (Ericsson & Ward, 2007). Many studies use a form of technology (e.g. television screens, computer monitors and video projector screens) to display performance with simulated responses (e.g. pressing a button or key and moving a joystick or mouse) to replicate the constraints of a real-world environment within a controlled research setting (Araujo, Davids, & Passos, 2007; Ericsson & Ward, 2007). For example, in sport, researchers may capture expert performance in the field using player and motion tracking systems or by developing assessments that simulate performance using forms of technology or virtual reality (Vaeyens, Lenoir, Williams, Mazyn, & Philippaerts, 2007). Importantly, expert performance is maximised under conditions that more closely replicate the performance context (Mann, Abernethy, Farrow, Davis, & Spratford, 2010; Müller et al., 2009).

The second stage identifies the underlying mechanisms with process-tracing measures, such as eye movement recordings and verbal reports (Kasper, 1998; Van de Wiel, 2017). Process-tracing measures are often implemented during performance to gain information about the mechanisms underlying expert performance (Ericsson, 2006; Kuusela & Pallab, 2000). For example, researchers can ask the participant to articulate their thoughts and reasons behind their behaviours during performance (Austin & Sutton, 2014; Ericsson, 2003). Notably, combining different process-tracing measures is typically required to cross-validate findings, which allows for a more comprehensive understanding about the mechanisms underlying expert performance (Afonso, Garganta, Mcrobert, Williams, & Mesquita, 2012; Van Gog, Paas, & Van Merriënboer, 2005).

The third stage is examining how expertise develops through practice history profiling, which elicits key information about the development milestones of an individual (Bell, 1997; Williams, Ward, Bell-Walker, & Ford, 2012). Commonly used methods include questionnaires, interviews, and logbooks, whereby participants retrospectively recall their learning activities over their career (Baker et al., 2018; Sosniak, 2006). For example, researchers can measure how much time an expert performer spent in different types of practice in a guided systematic environment (Baker, 2003; Baker, Cobley, & Fraser-Thomas, 2009; Côté, Baker, & Abernethy, 2003; Mattson & Richards, 2010). Information about the learning activities of an expert can be used by researchers and practitioners to develop training interventions to facilitate the development of expertise (Baker et al., 2003; Ericsson, 2006). Overall, studying expertise provides an insight into the potential of highly specific human behaviour, which often can only be attained by a very small portion of the general population (there are exceptions to this rule for generic skills such as walking, driving a car, reading, where a large proportion of the population reaches expert levels of performance, yet within those experts, expert performance can still be found e.g. Olympic speed walkers, Formula One drivers or speed readers).

Expert characteristics

Across various domains, including music, medicine, art, or sport, the characteristics that make an expert unique have been investigated extensively (Ericsson et al., 2018; Ericsson & Ward, 2007; Ericsson et al., 2007; Farrow et al., 2018; Littlepage & Mueller, 1997; Patel, Glaser, & Arocha, 2000; Starkes & Ericsson, 2003; Thomas & Lawrence, 2018). Most of this scientific body of literature is aimed towards understanding the strengths of an expert, i.e. the extent to which they display skills and characteristics that are not common in more novice performers (Ericsson, 2006; Gegenfurtner, Lehtinen, & Säljö, 2011; Klein & Hoffman, 1993; Mann, Williams, Ward, & Janelle, 2007; Voss et al., 2010; Wright, Bishop, Jackson, & Abernethy, 2010). Despite the overwhelming emphasis on the positive characteristics associated with expertise, it is worthwhile to acknowledge that experts also have their own shortcomings when it comes to performance (Anson, 2018;

Bouvet, Mottron, Valdois, & Donnadieu, 2016; Lintern, Moon, Klein, & Hoffman, 2018; Plucker & Levy, 2001; Sternberg & Frensch, 1992; Trafton & Hoffman, 2007). Therefore, understanding both the strengths and shortcomings of an expert provides a more comprehensive representation of expertise (Chi, 2006; Ericsson & Charness, 1994; Gobet, 2015). As such, the following section will discuss in detail the characteristics of an expert.

Expert strengths

Perceptual-cognitive skills

Whether it be a physician making the correct diagnosis of a disease within a clinical setting, or a soccer player selecting the most suitable team-mate that would directly lead to a goal scoring opportunity, making effective decisions is a fundamental requirement for expert performance across a wide range of domains (Connors, Burns, & Campitelli, 2011; Ericsson & Smith, 1991; Martindale & Collins, 2013; Norman et al., 2018; Travassos et al., 2013). Perceptual-cognitive skills (e.g. decision-making, anticipation, pattern recognition, visual selective attention, and strategic thinking, etc.) are integral to an individual's ability to make decisions and execute domain-specific skills in performance, particularly in domains whereby the performance environment is complex and rapidly changing (Araújo, Davids, & Hristovski, 2006; Mann, Williams, Ward, & Janelle, 2007; Williams, 2000). In some domains, such as sport, players are required to perform technical actions in a reciprocal and sequential manner (e.g. controlling the ball following a pass from a teammate, dribbling the ball into space, and taking a shot on goal), meaning that a phase of play can involve frequent decision-making moments that are continually adapted according to environmental constraints.

One of the main distinguishing factors among expertise within a sporting context is a player's ability to identify and process task-relevant information within the environment to execute the appropriate movement responses to the imposed task demands (Davids, Araújo, Correia, & Vilar, 2013; Travassos et al., 2012; Travassos, Araújo, Duarte, & McGarry, 2012). As such, experts display effective decision-making, which is reflected in faster response times and greater response accuracy when responding to a stimulus compared with novices (Araújo, Hristovski, Seifert, Carvalho, & Davids, 2019; Baker et al., 2003; Nakamoto & Mori, 2008; Ripoll et al., 1995; Vaeyens et al., 2007; Vaeyens et al., 2007). Also, experts demonstrate the ability to anticipate upcoming events, which is developed through extensive procedural and declarative knowledge compared with novices (Loffing & Cañal-Bruland, 2017; Savelsbergh et al., 2002; Williams & Jackson, 2019, 2019). Additionally, experts extract task-relevant information in a more efficient manner, which allows the athlete to direct their attention appropriately compared with novices (Mann, Causer, Nakamoto, & Runswick, 2019; Moran et al., 2002; Savelsbergh et al., 2002; Williams, Janelle, & Davids, 2004). Finally, experts can accurately recognise and recall key features of domain-specific patterns compared with novices (Abernethy, Baker, & Côté, 2005; Baker et al., 2003; Gorman, Abernethy, & Farrow, 2012, 2012). Collectively, effective decision-making allows experts to outperform their lesser skilled counterparts, with differences becoming more apparent in time-constrained environments (Den Hartigh, Van Der Steen, Hakvoort, Frencken, & Lemmink, 2017; Huijgen et al., 2015; O'Connor, Larkin, & Williams, 2016; Reilly, Williams, Nevill, & Franks, 2000; Vaeyens, Lenoir, Williams, Mazyn, & Philippaerts, 2007; Vaeyens, Lenoir, Williams, & Philippaerts, 2007; Verburgh, Scherder, van Lange, & Oosterlaan, 2014).

Error detection and correction

The capability to identify and correct one’s own movement is a performance characteristic that improves throughout practice (Causer et al., 2014; Ericsson, 2004; Kontogiannis & Malakis, 2009; Rossano, 2003). As a result, experts are more capable at detecting and correcting errors when evaluating their own performance when compared with novices (Benjamin, Mandel, & Kimmelman, 2017; Chi, Glaser, Rees, & Steinberg, 1982; Fakcharoenphol, Morphew, & Mestre, 2015; Spence & Brucks, 1997). For example, in sport, when expert and novice gymnasts walk across a balance beam as quickly as possible with or without vision (Robertson, Collins, Elliott, & Starkes, 1994). Both expert and novice gymnasts make more errors (i.e. unintentional deviations from a relaxed upright standing position) when compared with conditions where vision is available. However, expert gymnasts still can walk across the balance beam in the same amount of time, whereas novice gymnasts take almost two times longer in conditions without vision. In medicine, expert nurses were better at detecting and correcting errors during a dialysis procedure when compared with novice nurses (Wilkinson, Cauble, & Patel, 2011). Overall, experts use intrinsic feedback to detect and correct errors during performance, whereas lesser skilled individuals often rely on the extrinsic feedback provided by a teacher, coach, or mentor following performance (Ericsson, 2017, 2018; Sheridan & Reingold, 2017). As such, becoming an expert involves developing the ability to rapidly and efficiently correct movement errors (Desmurget & Grafton, 2000; Robertson et al., 1994; Rossano, 2003).

Cognitive effort

During the initial stages of learning, a novice will be more conscious about the aspects of performing a skill, whereas an expert is more proficient and will understand the amount of conscious attention required to be directed to other, more important aspects of performance, such as the patterning of opponents and positioning of teammates in sport (Ericsson, 2006; Fitts & Posner, 1967; Koedijker et al., 2011). As such, experts maintain a higher level of performance with less cognitive effort when compared with lesser skilled individuals performing the same task (Casakin, 2004; Ji-Ye Mao, 2000; Persky &

Robinson, 2017). For example, Shinar, Meir, and Ben-Shoham (1998) assessed the sign detection and recall performance of expert and novice drivers during manual shift and automatic transmission cars in a downtown area that required frequent gear shifting. Overall, expert drivers did not miss traffic signs compared with novice drivers, which highlights that until the skill of gear-shift driving becomes more efficient, performance is likely to be impaired (Shinar et al., 1998). Another example is in sport, whereby expert and novice baseball players were required to hit simulated pitches that varied in speed and height (Gray, 2004). However, when a secondary task (i.e. players were required to verbally identify an external tone as high or low) was introduced, novice baseball player performance (i.e. increase in swing errors) was more affected when compared with expert baseball players performance. Collectively, whether the nature of the task is simple or complex, experts often require less cognitive effort which allows them to be more adaptable to perform a task, even in instances when the attentional demands (i.e. secondary tasks) are introduced, when compared with novices (Beilock & Carr, 2001, 2004; Ericsson, 2003; Ericsson, 2006, 2006).

Speed-accuracy skills

Kicking a penalty in soccer, playing a song on a piano at a fast tempo, and speed typing all require fast and accurate movements to achieve successful performance (Andersen & Dörge, 2011; Palmer & Dalla Bella, 2004; van den Tillaar & Ulvik, 2014). Within these skills, a trade-off (i.e. increasing speed yields decreasing accuracy, and vice versa) between speed and accuracy often exists, whereby the speed at which a skill is performed is influenced by the movement accuracy demands (Bootsma, Marteniuk, MacKenzie, & Zaal, 1994; Fitts, 1954; Zhai, Kong, & Ren, 2004). However, in domains that require target-directed movements, the execution of a skill of an expert is less likely to be influenced by a speed-accuracy trade-off when compared with novices (Drake & Palmer, 2000; Fischer et al., 2016; Ripoll et al., 1995; van den Tillaar & Ettema, 2006). For example, in sport, expert golf players demonstrate shorter movement times with a minimal loss of accuracy under time-imposed situations (i.e. putt as fast as possible while still being accurate) when compared with novice golf players (Beilock, Bertenthal, Hoerger, & Carr, 2008). Another example is in the field of medicine, whereby expert surgeons demonstrate shorter movement times and higher levels of accuracy in a simulated medical procedure task when compared with residential surgeons and medical students (Liang et al., 2018). Overall, particularly in manual aiming skills, experts are less likely to be influenced by a speed-accuracy trade-off when time constraints are imposed on performance compared with novices (Proteau, 1992; Proteau & Marteniuk, 1993; Proteau, Marteniuk, & Lévesque, 1992).

Perceptual-motor abilities

Intelligence (i.e. ability to acquire and apply knowledge and skills), executive functioning (i.e. a set of cognitive processes that are necessary for cognitive control of behaviour), attentional control (i.e. the capacity to choose what to pay attention to and what to ignore), manual dexterity (i.e. coordinated movements of the hand and finger to grasp and manipulate objects), and speed of processing (i.e. responding to visual information) are perceptual-motor abilities that may be foundational to the development of expertise (Hambrick, Burgoyne, & Oswald, 2019). In chess, experts are often being reported with having a substantially higher intelligence quotient than lesser skilled players and the population mean (Gobet & Campitelli, 2002; Grabner, Stern, & Neubauer, 2007; Van Der Maas & Wagenmakers, 2005). In music, Kopiez and In Lee (2008) reported a significant correlation between a measure of perceptual speed and sight-reading performance in relatively skilled pianists. However, there was no significant correlation between fluid reasoning (i.e. a measure of the brains ability to take in new information without the benefit of practice or experience) and reaction time and sight-reading performance. In addition, Schellenberg and Weiss (2013) demonstrated that musically trained individuals typically score higher in an intelligence quotient assessment when compared with individuals with no music experience. In sport, the intelligence quotient of elite college football player players had no association with future National Football League performance (Lyons, Hoffman, & Michel, 2009). Furthermore, Voss et al. (2010) concluded that athletes have faster processing speed (i.e. shorter reaction times and overall shorter response times) in a variety of response time tasks, and are more efficient at attention allocation (i.e. focusing attention on task-relevant information and inhibiting attention allocation to task-irrelevant information) when compared with lesser-skilled athletes and individuals with no sporting background. Yet, there was no significant differences between groups in terms of their ability to utilise relevant visual cues (i.e. provides information where a stimulus is going to appear) and quickly disengage from irrelevant visual cues (i.e. provides incorrect information where a stimulus is going to appear) in the environment (Pashler & Shiu, 1999; Pashler, 1999; Posner & Fan, 2001). In medicine, Louridas, Szasz, de Montbrun, Harris, and Grantcharov (2016) demonstrated that some general measures of manual dexterity and spatial visualisation ability are associated with technical performance in minimally invasive medical procedures. Overall, it is likely that domain-general abilities may be foundational to the development of expertise but may not distinguish those with high levels of expertise from those with moderate levels of expertise (Beavan et al., 2020; Beavan et al., 2019; Hambrick et al., 2019; Roberts, 2008).

Expert shortcomings

Domain-specificity and context dependency

Experts are better at anticipating future events, predicting the outcome of an event, and adapting to situational changes during performance when compared with novices across a variety of domains (Goodwin & Wright, 2010; Mori & Shimada, 2013; Sohn & Doane, 2004; Williams & Ford, 2008). However, it is difficult for experts to outperform lesser skilled counterparts in domains whereby they have less experience in, or situations where task familiarity is lacking (Carmel & Bentin, 2002; Rienhoff et al., 2013; Sims & Mayer, 2002). For example, an expert chess player will be less accurate when recalling the location of chess pieces that are randomised on a chess board compared with recalling the locations of chess pieces only being in positions based on the traditional rules (Gobet & Simon, 1996; Reingold, Charness, Pomplun, & Stampe, 2001). Another example is in expert physicians who are typically better than novice physicians at identifying abnormalities in an X-ray or mammogram (Breckwoldt et al., 2012; Currie & MacLeod, 2017). However, similar performance is demonstrated by both expert and novice physicians in visual search and detection tasks, whereby a variation of the stimuli (i.e. recalling information that is randomised and not typically observed in traditional assessments) is implemented (Nodine & Krupinski, 1998; Van der Gijp et al., 2017). Overall, it is likely that experts will outperform novices in tasks they are familiar with, however performance differences are less likely to be evident in tasks that use a variation of the same stimuli (Adams, Rogers, & Fisk, 2013; Seamster, Redding, & Kaempf, 2000).

Overconfidence effect

Experts can be susceptible to an individual bias in which they believe the reliability of their own personal judgement is greater than the objective accuracy of a given situation (Dunning, 2011; Kruger & Dunning, 1999; Oskamp, 1965; Schlösser, Dunning, Johnson,

& Kruger, 2013). This phenomenon is commonly known as the Dunning-Kruger effect and has since Kruger and Dunning's original study in 1999 been applied to many fields, such as diagnostic medicine (Hodges, Regehr, & Martin, 2001), students' academic performance (Ryvkin, Krajč, & Ortmann, 2012), and logic reasoning (Pennycook, Ross, Koehler, & Fugelsang, 2017). For example, expert physicians who were relatively competent at diagnostics generally showed inflated self-assessments (Hodges et al., 2001). Similarly, university students who scored higher on academic midterm and final examinations still overestimated their performance (Kruger & Dunning, 1999; Ryvkin et al., 2012). Likewise, Pennycook et al. (2017) showed that participants from a general population who made more errors in a reasoning task overestimated their performance by a factor of three. Collectively, these studies confirmed that the Dunning-Kruger effect on cognitive tasks could result from an unawareness or indifference of an individual's bias. Overall, Kruger and Dunning (1999) attributed this deficit to a lack of metacognitive skills, whereby some experts may overestimate their ability because they are ignorant about their own capabilities (Aqueveque, 2018; Caspi et al., 2006; Dunning, 2011; Gibbs, Moore, Steel, & McKinnon, 2017; Huang, 2013; Iso-Ahola, La Verde, & Graefe, 1989).

Reliance on contextual information

Contextual information (i.e. data that gives context to a person, entity, or event) can come in many different forms, such as the strengths and weaknesses of an opponent and the conditions (e.g. weather forecast and court surface) of performance within a sporting context. In certain cases, experts rely on contextual information to make informed decisions (Benner, Hughes, & Sutphen, 2008; Murphy et al., 2016). For example, expert physicians are known to be more accurate in their diagnoses for a case when a patient's background (i.e. contextual information) is provided compared with novice physicians (Fried, Storer, King, & Lodder, 1991; Hobu, Schmidt, Boshuizen, & Patel, 1987).

However, when contextual information is limited or at times completely removed, the accuracy of diagnosis is lower in expert physicians (Jung et al., 2012; McRobert et al., 2013; Weiner et al., 2010). Another example is in sport, whereby tennis players often need to anticipate the upcoming events prior to the information becoming available within the environment (Triolet, Benguigui, Le Runigo, & Williams, 2013; Williams, Ward, Knowles, & Smeeton, 2002). During these situations, the availability of contextual information (i.e. postural information of the opponent) can facilitate anticipation (Huys et al., 2009; Rowe & McKenna, 2001; Singer, Cauraugh, Chen, Steinberg, & Frehlich, 1996). However, when expert tennis players are required to respond to situations where contextual information is removed, it often results in lower response accuracy scores (Murphy et al., 2016; Murphy, Jackson, & Williams, 2018). Perhaps the ability of an expert to make accurate decisions may be limited due to the amount of contextual information available within a given situation.

Misjudging lesser skilled counterparts

Given experts have experience as learners and a wealth of domain-specific knowledge, it is likely that experts would be adequate at predicting novice performance in the same domain (Camerer & Johnson, 1997; Larkin, McDermott, Simon, & Simon, 1980; Wolf, Sebanz, & Knoblich, 2018). However, a trade-off exists in the context of an expert being able to predict the ability of a lesser skilled counterpart, whereby the higher the expertise level, the worse they will be at predicting the performance of a novice (Dawes, 1971; Hinds, 1999; Johnson, 1988; Shanteau, 1984). Across a variety of domains, experts are often called upon to predict the performance of novices (Hinds, 1999; Wolf et al., 2018). For example, project managers predict team members times to complete new work assignments (Gersick, 1988), marketers and designers predict the consumers ability to learn new products and equipment (Erevelles, Fukawa, & Swayne, 2016), and a teachers predict a student's effort to complete homework and finish exams (Trautwein, Niggli, Schnyder, & Lüdtke, 2009). Consequently, because experts often underestimate a novice's ability to perform a task, it may result in employee isolation, failure to meet project deadlines, consumer dissatisfaction, and student frustration or boredom (Lehman, Matthews, D'Mello, & Person, 2008; Persky & Robinson, 2017). One of the main reasons behind an expert misjudging the ability of lesser skilled counterparts is because they find it difficult to take on the perspective of being a novice accurately (Cho, 2004; Hinds, 1999). It is only after performance has occurred that an expert's ability to predict the performance of a novice can become better calibrated (Bolger & Wright, 1994). Typically, there is a disconnect between peak knowledge (what I once knew) for current knowledge (what I now know) (Bolger & Wright, 1994).

Part 1 Section summary

Part 1 of literature review provided an introduction and perspective into expertise, defined what is an expert and highlighted the two primary aims of expertise research, which include assessing the characteristics of an expert and studying the development of expertise. Furthermore, Part 1 goes into depth about the interest in expertise research and briefly mentions some of the common ways to investigate expertise, which involve retrospective analyses, concurrent measures, an independent index of performance, and group-wise comparisons. Lastly, Part 1 details in-depth the characteristics of an expert, whereby it highlights the strengths associated with expertise, but also the shortcomings of an expert.

Part 2 – Assessing the characteristics of experts

Brief introduction and plan of development

Capturing expertise is a challenging task, particularly in domains where the nature of performance is dynamic and ever-changing (Belling et al., 2015; Pinder et al., 2015; Williams & Ericsson, 2005). At the present time, it is difficult to develop tasks that fully capture the complex interactions that occur between a performer, the environment, and the imposed task demands (Abernethy, 1988; Belling et al., 2015; Kanfer & Ackerman, 1989; Pinder et al., 2015). Consequently, current research methodologies aimed at assessing the characteristics of an expert with representative tasks are often associated with the decoupling of perception and action processes, poor information sources, and isolation tasks when aiming to assess the characteristics of an expert (Brunswik, 1956; Dhami, Hertwig, & Hoffrage, 2004; Dijkerman & De Haan, 2007; Mann et al., 2007; Pinder et al., 2011; Pinder, Renshaw, Headrick, & Davids, 2013). However, new technologies offer expertise researchers a wide range of tools whereby data can be collected in situ (Cianciolo et al., 2006; Pinder et al., 2015; Silvennoinen, Mecklin, Saariluoma, & Antikainen, 2009). Therefore, the following section will detail two of the most common methods employed by researchers to assess the characteristics of an expert, which include verbal protocols and the use of representative task designs.

Verbal protocols

Interviewing is a common method that can be used to investigate how an expert identifies and processes information to inform decision-making during performance (Ericsson, 2006; Halcomb & Davidson, 2006; Hopf, 2004). The main concern with interviewing is whether an expert can always articulate the thoughts and reasons behind their behaviours during performance (Austin & Sutton, 2014; Ericsson, 2003). This is primarily due to the fact that experts use intrinsic feedback to evaluate their own performance, whereas lesser skilled individuals often rely on extrinsic feedback provided by a teacher, coach, or mentor to evaluate performance (Ericsson, 2017, 2018; Sheridan & Reingold, 2017). Therefore, when experts are called upon to articulate the thoughts and reasons behind their decisions, it is often difficult due to the absence of any verbal rules and guidelines to use as reference (Kasper, 1998; Taylor & Dionne, 2000; Van de Wiel, 2017; Van Gog et al., 2005).

Originally published in 1893, Binet (1966) used verbal protocols (i.e. questionnaires and interviews) to assess the reasons behind the decision-making processes of expert chess players. However, there was a lack of consistency among experts when asked to describe the strategies behind their decisions in performance (Binet, 1966). Furthermore, Watson (1913) questioned the reliability of the data when using introspection and identified that discrepancies exist between the thoughts and reasons reported following performance and the behaviours observed during performance in human behaviour. Furthermore, Watson (1913) argued that it allows participants to evaluate their own processes, whereby they can compare their decisions with past experiences (Ericsson & Simon, 1980; Van Someren, Barnard, & Sandberg, 1994). Therefore, to minimise the effects that introspection may have on the reliability of the data, there was a transition towards methods which involved asking participants to think aloud and give immediate verbal feedback behind their decisions during performance (Duncker & Lees, 1945; Van de Wiel, 2017; Watson, 1920).

Think aloud protocols or methods that require the participant to provide immediate feedback involve recording and transcribing the exact words when a participant is explaining the thoughts and reasons behind their decision-making in the moment (Fonteyn, Kuipers, & Grobe, 1993; Hopf, 2004; Kuusela & Pallab, 2000; Van de Wiel, 2017). One of the advantages of using think aloud protocols or methods that require the participant to provide immediate verbal feedback is that it minimises the opportunity for them to theorise and rationalise their thoughts and reasons behind their decisions and keeps the time to respond to a minimum (Fonteyn et al., 1993; Jääskeläinen, 2010). Overall, using verbal protocols typically provides more reliable information about the problem-solving mechanisms that underlie expert performance (Kuusela & Pallab, 2000; Posner, 1989; Samson, Simpson, Kamphoff, & Langlier, 2017; Smagorinsky, 1989). However, it is important that participants are not aware beforehand that they will be required to report the thoughts and reasons behind their decisions during performance (Ryan & Haslegrave, 2007; Van de Wiel, 2017). Therefore, verbal protocols are a useful method to gain information about the mechanisms underlying expert performance (Ackerman & Thompson, 2017; Graesser et al., 2018).

Representative task designs

Another way for researchers to assess the characteristics of an expert is to assess performance in tasks that accurately describe and measure performance under specific task constraints that effectively capture the functional responses of performers in situations that represent performance (Ericsson & Lehmann, 1996; Helsen & Starkes, 1999; Williams & Ericsson, 2005). However, researchers have argued that much of our current understanding may be derived from methods that do not fully capture experts demonstrating expertise (Dicks, Button, & Davids, 2010; Ericsson & Smith, 2011; Pinder et al., 2011; Van der Kamp, Rivas, Van Doorn, & Savelsbergh, 2008). Typically, researchers often divide performance into components to identify the key factors related to expert performance (Ericsson, 1998, 1999, 2005; Ward, Williams, & Hancock, 2006). More specifically, within a sporting context, researchers often reduce performance into skills and developed tasks in an attempt to quantify expertise (Elferink-Gemser, Visscher, Lemmink, & Mulder, 2007; Huijgen et al., 2014; Phillips et al., 2010; Vaeyens, Lenoir, Williams, & Philippaerts, 2008). For example, researchers may develop film-based simulations of offensive patterns of play to assess the decision-making ability of a soccer player (Vaeyens et al., 2007; Vaeyens et al., 2007). A projector can display the visual field from a players perspective with near-life-size images (Vaeyens et al., 2007; Vaeyens et al., 2007). Pressure-sensitive sensors can be located underneath each participants feet and ball to measure their initiation of response (Vaeyens et al., 2007; Vaeyens et al., 2007). Yet, there is a trade-off that occurs when dividing performance into components, whereby the more general a task is, the more likely it is to lack external validity (Parsons, 2015).

As a result, researchers are faced with a range of issues and challenges when designing representative tasks aimed at assessing the characteristics of an expert (Farrow et al., 2018; Pinder et al., 2015; Williams & Ericsson, 2005). On one side, non-representative designs in a laboratory setting allow for high degrees of experimental control (Berkowitz & Donnerstein, 1982; Brunswik, 1947, 1956; Dicks et al., 2009). Whereas representative designs in a field setting, also referred to as in situ can allow for better replication of performance, however experimental control is more difficult (Belling et al., 2015; Brunswik, 1955; Causer et al., 2014; Ericsson & Lehmann, 1996; Pinder et al., 2011; Travassos et al., 2013; Voss et al., 2010). Despite this, expert performance is maximised under conditions that more closely replicate the performance context (Mann et al., 2010; Müller et al., 2009).

Despite the inherent shortcomings (e.g. decoupling of perception and action processes, poor information sources, and isolation tasks) with replicating performance of real-world environment within a controlled environment, advancements in technology offer a range of tools for researchers to develop more representative tasks (Ericsson & Smith, 2011; Williams & Ericsson, 2005). For example, researchers may develop a flight simulator task to assess an aviator's decision-making and flight control performance (Kennedy et al., 2010). The task itself can incorporate motion, vibration and sound elements that would be experienced during a real-world environment (Taylor et al., 2007). Furthermore, a pilot's perspective of a real-world visual environment can be generated and displayed by a form of technology, whereby the aircrafts position and communication frequencies can be regularly updated (Taylor et al., 2005). This particular example highlights how effective a representative task design can be at capturing and replicating performance under specific task constraints, which elicits the functional responses of performers in situations that represent performance.

Part 2 section summary

Part 2 detailed two of the most common methods employed by researchers to assess the characteristics of an expert, which include verbal protocols and the use of representative task designs. Evidently, Part 2 discussed the difficulties with capturing expertise, more so in domains where performance is dynamic and ever-changing (Belling et al., 2015; Pinder et al., 2015; Williams & Ericsson, 2005). Currently, it is difficult for researchers to develop tasks that fully capture the complex interactions that occur between a performer, the environment, and the imposed task demands (Abernethy, 1988; Belling et al., 2015; Kanfer & Ackerman, 1989; Pinder et al., 2015). This is concerning as the differences in performance between an expert and novice is maximised under conditions that more closely replicate the performance context (Mann et al., 2010; Müller et al., 2009). However, over the last several years, improvements in technology have offered a range of tools for researchers to develop more representative tasks, such as developing a flight simulator task to assess an aviators decision-making and flight control performance (Ericsson & Smith, 2011; Williams & Ericsson, 2005).

Part 3 – Studying the development of expertise

Brief introduction and plan of development

As the proportion of a population who become experts is very small, predicting who will become an expert is nearly impossible (Camerer & Johnson, 1997; Dew, Read, Sarasvathy, & Wiltbank, 2009). As a result, researchers typically recruit experts and ask them to reflect on their personal learning histories (Sosniak, 2006; Tynjälä, Nuutinen, Eteläpelto, Kirjonen, & Remes, 1997; Voss & Wiley, 2006). The majority of these studies require an individual to think back over many years, if not, decades, and detail the specific involvements in various activities (McCormack, Manley, & Titchen, 2013; Sosniak, 2006; Ward et al., 2007). However, this approach can be influenced by recall bias and memory recall ability, therefore careful interpretation is recommended when using retrospective methods to examine the development of expertise (Baker et al., 2018; Hayman, Polman, & Taylor, 2012; Hodge & Deakin, 1998; Howard, 2011, 2012). Therefore, the following section will describe the frequently used methods by researchers to study the development of expertise, which include retrospective recall and concurrent learning activities.

Retrospective recall

Researchers use different methods of retrospective recall (e.g., interviews, questionnaires, and diary reports) to gain information about the development of expertise, whereby an individual recalls data on their learning activities experienced throughout their career (Baker et al., 2018; Côté et al., 2007; Sosniak, 2006; Van de Wiel, 2017; Ward et al., 2007). Qualitative interviews involve a researcher conducting a one-on-one interview with an expert and at times, with a parent and/or coach if necessary (Coutinho, Mesquita, Davids, Fonseca, & Côté, 2016; Swallow et al., 2015). Typically, the interview contains a sequence of open-ended questions related to the individuals learning history (Anquinet et al., 2015; Wright & Côté, 2003). Advantages with conducting qualitative interviews is the detail of information that can be gathered, and any responses that require clarification can be directly addressed (Baker et al., 2018; van Selm & Helberger, 2019). Despite this, conducting, and analysing data obtained from qualitative interviews can be time consuming and requires large sample sizes (Baker et al., 2018).

Quantitative questionnaires provide an alternative approach to the difficulties (i.e., time consuming and requires large sample sizes) associated with conducting qualitative interviews (Hopwood, Farrow, MacMahon, & Baker, 2015; Yoshikawa, Weisner, Kalil, & Way, 2008). Typically, quantitative questionnaires involve a participant completing an in-depth questionnaire that is designed to obtain a more comprehensive understanding about an individual's learning history (Baker et al., 2018). Quantitative questionnaires are administered in a pencil-and-paper or electronic format to be completed in a supervised setting (i.e., supervisor present to assist and provide instructions) or unsupervised setting (i.e., location of the participants choosing). Consequently, quantitative questionnaires have less control when it comes to the quality of responses, yet it is easier to administer and data analysis is more efficient when compared with qualitative interviews (Baker et al., 2018). Despite the advantages and disadvantages, both retrospective methods require an individual to think back and remember the very specific details of their past. As a result, there are some limitations with using both retrospective recall methods to study the development of expertise, particularly in domains where careers can span over many years (Baker et al., 2018; Hayman et al., 2012).

Overall, the major concern is with the validity and reliability of the data obtained, as the data can be confounded by the memory recall ability of a participant (Baker et al., 2018; Cumming, Hall, & Starkes, 2005). Previously, researchers have reported that individuals tend to overestimate the quantity and time of practice for more recent achievements and underestimate the quantity and time of practice for more distant achievements (Baker et al., 2018; Howard, 2011; Kemp, 1988). Although conducting a prospective developmental study over an extended period of time with a large cohort with the intention of identifying a select few that become an expert is a potential solution, it is still difficult given a small proportion of a population will become an expert (Wagner & Stanovich, 1996). Even so, researchers have reported that when following the development of child prodigies, it is difficult to ascertain when and if they will become an expert (Feldman & Goldsmith, 1986; Goldsmith, 2000). Although the use of retrospective recall may have its flaws, researchers continue to inform the latest and most suitable ways to best apply the different methods of retrospective recall for research purposes (Côté et al., 2005).

Concurrent learning activities

Documenting the learning activities of an individual as it happens over a period of time is a more effective approach to examine the development of expertise when compared with retrospective recall methods (Deakin, Côté, & Harvey, 2006; Ericsson, 2006). Typically, self-reported activities and observation reports are commonly used methods that provide more reliable data about the learning activities of an individual (Baker et al., 2018; Charness, Tuffiash, Krampe, Reingold, & Vasyukova, 2005; Cunningham, Zibulsky, Stanovich, & Stanovich, 2009; Miksza, 2007; Rondinelli, Omery, Crawford, & Johnson, 2014; Tedesqui & Young, 2017). Overall, researchers are often interested in examining the quantity of a type of practice an individual engages in or more specifically, the details about the practice itself (Baker et al., 2003; Baker et al., 2018; Deakin et al., 2006; Dunn & Shriner, 1999; Williamon & Valentine, 2000).

Eliciting information about the learning activities concurrently usually follows a form of quasi-longitudinal study design (e.g. longitudinal and cross-sequential), whereby researchers collect repeated observations of the same variables over a short or long period of time (Deakin et al., 2006; Ericsson, 2006). Examining the learning activities concurrently provides information about the relevance that the microstructure and macrostructure of daily activities has on the development of expertise (Deakin et al., 2006; Ericsson, 2006). For example, in sport, researchers may examine the practice activities that a player engages in on a weekly basis, some of which include coach-led practice, peer-led play and individual practice (Güllich, 2019; Larkin, O'Connor, & Williams, 2016, 2016). When examining the details about the practice itself, variables of interest may be measuring the time spent practicing a set-play or time spent focusing on developing a domain-specific skill, such as technique (e.g. ball control, dribbling, and passing) in soccer (Ford, Yates, & Williams, 2010; Güllich, 2019). In chess, researchers may examine the number of weekly practice hours, or more specifically, practice that involves the serious analysis of positions alone (Charness, Krampe, & Mayr, 1996; Gobet & Campitelli, 2007; Howard, 2012). In medicine, researchers may be interested in measuring the number of hours spent at lectures and seminars to examine the association between education and expertise in nurses (Snelling, Lipscomb, Lockyer, Yates, & Young, 2010). Overall, information about the learning activities of an expert can be used by researchers and practitioners to develop training interventions to facilitate the development of expertise (Ward et al., 2007)

The main limitation with examining the concurrent practice activities of an expert over an extended period of time is that it requires a substantial amount of resources to be conducted, which likely explains the relatively few longitudinal and prospective studies that exist (Patel et al., 2003). Consequently, researchers continue to seek for alternative means to examine practice activities concurrently (Abernethy et al., 1993; Ward et al., 2007). More recently, technological advances, such as the widespread use of mobile devices and accessibility to internet access allows researchers to have greater data collection power (Baker et al., 2018). Utilising recent technological advances could lead to significant developments in our understanding about the development of expertise (Baker et al., 2018).

Part 3 section summary

Part 3 described the frequently used methods by researchers to study the development of expertise, which include retrospective recall and concurrent learning activities. Part 3 highlighted that given a small proportion of a population who become experts are very small, researchers often rely on an expert to reflect on their personal learning histories (Sosniak, 2006; Tynjälä et al., 1997; Voss & Wiley, 2006). Although measuring learning activities concurrently minimises the influence of recall bias and memory recall ability, which can increase the validity and reliability of the data and our understanding about the association between practice and the attainment of expertise (Baker et al., 2018; Côté et al., 2007; Sosniak, 2006; Van de Wiel, 2017; Ward et al., 2007). However, conducting longitudinal study designs over a period of time is often limited by a lack of resources (Baker et al., 2018). Therefore, expertise researchers are seeking alternative methods (i.e. technological advances) to further improve our understanding about the development of expertise (Abernethy et al., 1993; Ward et al., 2007).

Part 4 – Factors influencing the development of expertise

Brief introduction and plan of development

While there are many factors (e.g. genetics, training, and psychological traits/skills) that underlie expertise, two of the main factors that influence the development of expertise is a guided systematic training environment and the amount of domain-specific practice an individual engages in (Baker & Horton, 2004; Ericsson, 2006). When people are introduced to a domain they have no or little experience in, an individual will tend to complete the domain-related requirements under the supervision of someone that is has more experienced than themselves. Working independently is possible once an acceptable level of competence is attained, which often occurs after months or years of experience depending on the domain (Teijeiro, Rungo, & Freire, 2013). At this stage of development, an individual will either maintain this level of competence or continue to seek improvements to become an expert (Persky & Robinson, 2017). Therefore, it is likely that improving beyond an acceptable level of competence requires deliberate and purposeful efforts. As such, the following section highlights certain factors that may influence the development of expertise, in particular is the access to guided systematic training environments and the importance of domain-specific practice.

A guided systematic training environment

The development of expertise reflects a complex and dynamic interaction that occurs between the natural abilities, intrapersonal skills, and environmental factors of an individual (Ericsson, Nandagopal, & Roring, 2009; Gagné, 2004, 2009). Underlying this interaction are certain catalysts (i.e. intrapersonal, environment and chance), which can accelerate or hinder the development of expertise (Baker & Horton, 2004; Gagné, 2004). The influence of a guided systematic training environment is a commonly reported catalyst that can confound the development of expertise in various domains (Barab & Plucker, 2002; Burgess & Naughton, 2010). Typically, individuals that demonstrate a natural ability to do something are identified at a relatively early age and chosen to undergo a guided and structured training program in a specialised environment (Subotnik & Jarvin, 2005; Williams & Reilly, 2000).

Implementations of guided systematic training environments can be observed in a wide variety of domains, such as music (i.e. music academies and conservatives), education (i.e. selective schools for gifted and talented students) and sport (i.e. sports schools and talent development programs). Guided systematic training environments provide access to high-quality instructional resources (i.e. knowledgeable coaches and specialised coaching), whereby the aim is to effectively facilitate the development of expertise (Baker & Horton, 2004; Gagné, 2015; Oreck, Baum, & McCartney, 2000). Previously, in sports, the amount of time spent with an instructor has been identified as a crucial aspect of an athlete's overall development, whereby it is likely that knowledgeable coaches create an environment that fosters optimal learning (Baker et al., 2003; Christensen, 2014; Deakin & Cobley, 2003; Young, 1998). In addition, Leas and Chi (1993) demonstrated that in swimming, expert coaches were more direct and precise with their assessment of performance and recommendations for improving performance when compared with novice coaches.

Overall, it is likely that access to high-quality instructional resources can assist with the development of expertise. However, access to guided systematic training environment also highlights the important role that families, significant others, and particularly the parents play in the development of expertise (Baker & Horton, 2004; Bloom, 1985; Côté, 1999; Côté et al., 2003). Although parental involvement changes as a child ages and becomes more skilful, it is during the initial stages of involvement where parents are required to provide significant support (Baker & Horton, 2004). Initially, parents enrol their child into a guided systematic training environment to have access to high-quality instructional resources, organise transport to and from practice sessions (i.e. whereby the geographical location can create accessibility issues), and provide financial support (Olszewski-Kubilius, 2018; Witte, Kiewra, Kasson, & Perry, 2015). Furthermore, parents pay substantial ongoing fees to maintain their child's position within the guided systematic training environment, which can create unequal opportunities for individuals from lower socioeconomic backgrounds (Wolfenden & Holt, 2005). Collectively, access to high-quality instructional resources and significant family support likely confound the development of expertise.

The importance of domain-specific practice

The theory of deliberate practice is a framework that details how practice may lead to improvements in performance and the attainment of expertise (Ericsson, 2004, 2006, 2015; Ericsson & Charness, 1994; Ericsson et al., 1993; Ward et al., 2007). Deliberate practice is defined as practicing with the intent of improving specific aspects of performance (Ericsson & Harwell, 2019; Ericsson et al., 1993; Miller et al., 2020). Ericsson et al. (1993) first introduced the term deliberate practice when they examined the activities of musicians (e.g. violinists and pianists) since the commencement of their musical journey until their time enrolled in a music academy. The music students were subdivided into groups (e.g. best and good) according to performance, which was based on the likelihood of that individual becoming a professional musician later in their career according to the professors in the music academy. In addition, both the activities of "best" and "good" group were compared with students who were studying to become music teachers in the education department. Lastly, a fourth group, which was the expert group was later introduced and involved professional pianists that were currently playing in a world-class orchestra. Across all expertise groups, participants retrospectively recalled in qualitative interviews and diary reports the number of hours spent in music activities since the beginning of their music journey until the present day.

The number of hours in solitary music practice (i.e., practicing alone) by 18 years of age was compared between groups, as it was subjectively rated by the participants as the most relevant type of practice to improve performance when compared with other types of practice (i.e. group practice, lessons, and learning about music theory). The mean start age for expert pianists was 5.8 years of age, compared with a mean start age of 7.9 years of age for the other groups. When analysing the amount of solitary music practice between the groups, the experts had accumulated 7,410 hours, the good violinists had accumulated 5,301 hours, and the music teachers had accumulated 3,420 hours by 18 years of age. Consequently, the authors hypothesised that expertise is directly related to the number of deliberate practice hours accumulated. However, it is important to note that measures of performance were determined at one point of time (i.e. current skill level determined by an external source), rather than being tracked across development.

Despite this, the data that was collected from this pioneering work was to provide information about how practice increases over time and the relationship it has with the attainment of expertise and how this type of activity can be defined. As a result, it was proposed that extended bouts of engagement and practice which is deliberate and purposeful is necessary to attain expert status in any domain (Ericsson, 2003; Ericsson, 1999, 2004, 2005, 2006; Ericsson & Charness, 1994; Ericsson & Harwell, 2019; Ericsson et al., 2018; Ericsson et al., 1993; Ericsson & Lehmann, 1996; Ericsson & Smith, 1991; Ericsson et al., 2007; Macnamara & Maitra, 2019; Starkes & Ericsson, 2003; Williams & Ericsson, 2005). Furthermore, it was proposed that a minimum of ten years' experience, or 10,000 hours is required to become an expert (Ericsson, 2003; Ericsson, 1998; Ericsson & Lehmann, 1996; Ford, Ward, Hodges, & Williams, 2009).

Since the pioneering work of Ericsson et al. (1993), many researchers have reported that despite being attractive at face value, the number of years of experience and the amount of hours required to become an expert differs (i.e. exceeds or is less than 10,000 hours or 10 years' experience) across domains (Horton, Baker, & Schorer, 2008). For example, in sport, international Belgium soccer players that compete at a professional level had accumulated approximately 7,000 hours of practice by 20 years of age (Helsen, Starkes, & Hodges, 1998). Furthermore, expert Australian national team sports players reported an average of 3,939 hours of practice accumulated by 19 years of age (Baker et at., 2003).

In addition, instances were 10,000 hours or 10 years' experience has been far exceeded can be observed in Olympic gymnasts from Canada had accumulated 18,835 hours of practice by the time they were 16 years of age (Law, Côté, & Ericsson, 2007). Another example is in chess, whereby expert chess players self-reported that 3,016 to 23,606 hours of practice is required to reach master status (Gobet & Campitelli, 2007). Evidently, there are certain cases of skilled individuals reaching the highest level of expertise with less than ten years of experience and less than 10,000 hours of practice accumulated at a much younger age than what would typically be observed. Therefore, the notion that a minimum of ten years or 10,000 hours of practice is required to become an expert should be followed cautiously, as evidence suggests it is possible to attain expertise in much less time. Despite this, it is still likely that systematic and consistent engagement in practice that is deliberate and purposeful is the optimal way to develop expertise across a variety of domains.

Part 4 section summary

Part 4 highlighted certain factors that may influence the development of expertise, in particular is the access to guided systematic training environments and the importance of domain-specific practice. Overall, improving beyond an acceptable level of competence likely requires deliberate and purposeful efforts (Baker & Horton, 2004; Ericsson, 2006). Furthermore, guided systematic training environments provide access to high-quality instructional resources (i.e. knowledgeable coaches and specialised coaching) that can facilitate the development of expertise (Baker & Horton, 2004; Gagné, 2015; Oreck et al., 2000). Collectively, access to high-quality instructional resources and significant family support likely confound the development of expertise.

Part 5 – Implications for future research in expertise

Although expertise research started several decades ago, there are many drawbacks that remain present in current practice when assessing the characteristics of an expert and studying the development of expertise (Baker et al., 2018; Deakin et al., 2006; Ericsson & Smith, 1991; Farrow et al., 2018; Pinder et al., 2015). In terms of assessing the characteristics of an expert, the key issues, and challenges in the development of representative tasks were discussed in detailed. There are several areas which researchers can improve upon when developing tasks that accurately describe and measure performance under specific task constraints that effectively capture the functional responses of performers in representative situations (Ericsson & Lehmann, 1996; Helsen & Starkes, 1999; Williams & Ericsson, 2005). Given expert performance is maximised under conditions that more closely replicate the performance context (Farrow et al., 2018; Pinder et al., 2015), it is crucial that researchers aim to design representative tasks with high action fidelity and high functionality relevant to the domain (Araujo et al., 2007; Pinder et al., 2011). As such, researchers are encouraged to embrace new technologies that allow for the assessment of expertise in more representative and competitive contexts (Campbell, Toth, Moran, Kowal, & Exton, 2018; Farrow et al., 2018; Stout, Passingham, Frith, Apel, & Chaminade, 2011; Towne, Ericsson, & Sumner, 2014; Williams, Ford, Eccles, & Ward, 2011). Within these tasks, there will be an increase in the amount of contextual information, scenarios, and behaviours that would be observed in a real-world environment compared with laboratory settings (Araujo et al., 2007; Gleeson & Kelly, 2020; Krause, Farrow, Buszard, Pinder, & Reid, 2019; Murphy et al., 2016; Runswick et al., 2018).

Similarly, the key issues, and challenges with studying the development of expertise were also discussed in detail throughout the literature review. As experts make up a relatively small cohort of a much larger population, the main issue from a researcher's perspective is predicting who will become an expert is nearly impossible (Camerer & Johnson, 1997; Dew et al., 2009). Consequently, the validity and reliability of the data derived from certain methods (e.g., verbal protocols and retrospective recalls) remains questionable (Baker et al., 2018; Baker, Young, Tedesqui, & McCardle, 2020; Hayman et al., 2012; Hopwood, MacMahon, Farrow, & Baker, 2016; Hopwood, Baker, MacMahon, & Farrow, 2011; Leite, Baker, & Sampaio, 2009; Ward et al., 2007). Despite the strengths of longitudinal study designs, they often require significant time and resources, which is typically not available to researchers or practitioners (Taylor et al., 2007; Ward et al., 2007). As such, researchers are encouraged to seek alternative methods that allow for a better insight into the types of practice and activities that are most related with the attainment of expertise, both over short and long periods of time. While the quality of research continues to improve, our knowledge about the development and assessment of expertise in human behaviour will continue to expand. In addition, researchers may seek to explore expertise in different domains to further broaden and deepen our understanding about expertise in human behaviour. Interestingly, esports appears to be a domain that has emerged relatively recently and can potentially offer new insights into how expertise develops, can be measured, and is influenced by confounders.

Part 6 – The rise of esports

Playing video games is a very popular recreational activity among children, adolescents, adults, and the elderly (Biddiss & Irwin, 2010; Das, Zhu, McLaughlin, Bilgrami, & Milanaik, 2017; Durkin, Boyle, Hunter, & Conti-Ramsden, 2015; Goldstein et al., 1997). Over the last several decades, video games have evolved from arcade games (i.e. Tetris, Space Marines, and Pong) into multiplayer online game environments (i.e. Counter-Strike: Global Offensive, League of Legends, and Dota 2) (Dale & Green, 2017).

Nowadays, millions of players worldwide simultaneously compete against video game bots (i.e. a type of artificial intelligence-based expert system software that plays a video game in the place of a human) or against other humans (Jang & Byon, 2019). Over time, competitive video game playing has become professionalised (i.e. international tournaments, sponsored teams, and worldwide audiences), and for a minority of players, it is now a career option for those that compete at the highest level of competition (Martončik, 2015; Zhao & Zhu, 2020). This type of competitive video gaming has been defined as esports, which typically involves individuals and/or teams of highly skilled players who compete in a form of organised video game competitions through human-computer interactions (Hamari & Sjöblom, 2017; Pluss et al., 2019; Wagner, 2006).

Esports is a relatively new domain that has emerged from video game culture and is rapidly becoming one of the most popular areas in today's technology-driven society (Muriel & Crawford, 2018). The increase of awareness about esports has also sparked interest in researchers, whereby researchers are interested in exploring the psychology of esports and the advantages that esports presents to the field of expertise (Bányai et al., 2019; Cottrell et al., 2019; Pedraza-Ramirez et al., 2020; Pluss et al., 2019). The use of dynamic visual displays, the demand on flexible attention allocation, and the requirement for precise time-constrained bimanual motor coordination makes esports a unique medium for studying expertise (Toth, Frank, Putrino, & Campbell, 2021). From an expertise researcher's perspective, as esports is mediated by forms of technology for both competition and training, the perception-action coupling experienced during performance can be accurately replicated in a controlled laboratory setting. Researchers can customise in-built settings within the software used in esports to develop highly controlled and domain-specific training interventions without sacrificing task representativeness (Boot, Sumner, Towne, Rodriguez, & Anders Ericsson, 2017; Towne et al., 2014).

Recently, researchers have documented the cognitive benefits that video game experience can have on an individual (Granic, Lobel, & Engels, 2014; Green & Bavelier, 2006). Video game experience has been associated with improvements in basic visual processes, whereby 50 hours of action video game play spread over 10 to 12 weeks improved visual contrast sensitivity (i.e. the ability to distinguish subtle differences in shades of grey) compared with a group undertaking no video gaming (Li, Polat, Makous, & Bavelier, 2009). Improvements in attention and vigilance, whereby video game experience improved performance on the ability to quickly locate a target stimulus in a field of distractors, keeping track of a set of moving objects that were visually identical to other moving objects in the visual field, and refraining from responding to non-target stimuli in a situation in which most stimuli required a response but an occasional stimulus called for no response (Dye, Green, & Bavelier, 2009; Green & Bavelier, 2012; Trick, Jaspers-Fayer, & Sethi, 2005). Improvements in executive functioning, whereby individuals with video game experience demonstrated a superior ability to switch rapidly and without error between tasks that have conflicting demands (Anderson, Bavelier, & Green, 2010; Colzato, van den Wildenberg, & Hommel, 2014; Green & Bavelier, 2012). While 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. 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 et al., 2014; Stafford & Dewar, 2014). Therefore, researchers would benefit from a theoretical outline to guide future expertise research in esports.

Conclusion

Overall, the purpose of the literature review was to provide an introduction and perspective into expertise along with the ways that researchers have sought to study it.

Part 1 introduced the interest in expertise research, outlined how to study expertise and described what are the characteristics of an expert. Part 2 detailed the methods for assessing the characteristics of an expert, such as the use of verbal protocols and the use of representative task designs. Part 3 described methods for studying the development of expertise, such as retrospective recall and concurrent practice activities. Part 4 explained the factors that may influence the development of expertise, such as a guided systematic training environment and the importance of domain-specific practice. Collectively, Part 5 highlighted the main obstacles which limit current expertise research and details the implications for future research in expertise. Lastly, Part 6 provides a brief description of the rise of competitive video gaming and how a new domain known as esports has evolved.

Overall, the evolving and dynamic nature of expertise has made it difficult to develop a suitable methodology, that controls for confounders while examining experts in contexts that are specific to their expertise domain. As such, it is important that future research investigates new, practical, reliable, and valid assessment protocols to continue improving the quality of research. While the research described in this literature review has provided researchers with invaluable insights into how expertise is acquired in a wide variety of domains, expanding on these findings in different expertise domains may further broaden and deepen our understanding about the development and assessment of expertise in human behaviour. Esports appears to be a domain that has emerged relatively recently and can potentially offer new insights into assessing the characteristics of an expert and studying the development of expertise.

Chapter 3:

Study 1

Esports: the chess of the 21st century

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Abstract

For many decades, researchers have explored the true potential of human achievement. The expertise field has come a long way since the early works of de Groot (1965) and Chase and Simon (1973). Since then, this inquiry has expanded into the areas of music, science, technology, sport, academia, and art. Despite the vast amount of research to date, the capability of study methodologies to truly capture the nature of expertise remains questionable. Some considerations include (i) the individual bias in the retrospective recall of developmental activities, (ii) the ability to develop ecologically valid tasks, and (iii) difficulties capturing the influence of confounding factors on expertise. This article proposes that expertise research in electronic sports (esports) presents an opportunity to overcome some of these considerations. Esports involves individuals or teams of players that compete in video game competitions via human-computer interaction. Advantages of applying the expert performance approach in esports include (i) developmental activities are objectively tracked and automatically logged online, (ii) the constraints of representative tasks correspond with the real-world environment of esports performance, and (iii) expertise has emerged without the influence of guided systematic training environments. Therefore, this article argues that esports research provides an ideal opportunity to further advance research on the development and assessment of human expertise.

Keywords: electronic sports, expertise, expert performance, excellence, skilled performance, video games, gaming

Introduction

Exploring the boundaries of human performance has fascinated researchers and practitioners in a range of fields and domains (Ericsson & Smith, 1991; Gagné, 2004, 2013; Williams & Ericsson, 2005). Decades ago, de Groot (1965) and Chase and Simon (1973) investigated the complex thoughts and processes of expert chess players. Since then, the expert performance approach has been applied to sport (Côté et al., 2007; Starkes & Ericsson, 2003; Williams & Ericsson, 2005), music (Ericsson et al., 1993; Lehmann & Ericsson, 1997; Tang & Giddins, 2016), medicine (Ericsson, Whyte IV, & Ward, 2007; Gordon, 1988; Tang & Giddins, 2016) and art (Augustin & Leder, 2006; Mullennix & Robinet, 2018). The aim of the expert performance approach is to identify the key characteristics of an expert and understand how expertise is developed over time (Charness & Tuffiash, 2008; Ericsson & Smith, 1991). According to the expert performance approach, capturing human expertise has three distinct stages (Ericsson & Smith, 1991; Williams & Ericsson, 2005). The first stage involves capturing expert performance of a real-world environment in laboratory-testing (e.g. video/film and virtual reality) and/or field setting (e.g. match analysis and simulations). The second stage identifies the underlying mechanisms with process-tracing measures (e.g. visual search behaviour, film occlusion and verbal reports). The third stage is examining how expertise develops through practice history profiling (e.g. questionnaires, interviews, and logbooks) and learning studies (e.g. training interventions). Although the expert performance approach offers a theoretical guide to investigate expertise, considerations about the application of the approach have been raised (Williams & Ericsson, 2005).

Capturing the skills that define expertise within any domain is a hallmark of the expert performance approach (Ericsson & Smith, 1991; Williams & Ericsson, 2005). This becomes a challenge in domains where a clear and measurable performance outcome is lacking (Williams & Ericsson, 2005). For example, in sport, behavioural constructs (e.g. anticipation and decision-making) are difficult to assess within a controlled laboratory setting under standardised conditions (Afonso et al., 2012; Williams & Ericsson, 2005). The difficulty here is developing representative tasks that correspond with the constraints of a real-world environment. This consideration will influence the range of methodologies researchers develop to identify the key characteristics of experts (Ericsson & Smith, 1991; Williams & Ericsson, 2005). Whether distinguishing differences between skill groups or predicting superior performance, the lack of task representativeness has the potential to undermine the validity and reliability of the data. Another consideration is that expertise is largely influenced by external factors, such as talent development programs (e.g. sporting organizations or selective schools) and the guidance of a mentor (e.g. sporting coach or music teacher). Yet, researchers have difficulties capturing the interaction of these confounders towards the development of expertise (Baker et al., 2003). The interrelationship between these factors can complicate our interpretation about the nature of expertise. It has been recommended that future research should embrace new technology that can simulate the constraints of a real-world environment within a controlled laboratory setting, while also collecting accurate and reliable data (Boot, 2015; Boot et al., 2017; Williams & Ericsson, 2005). Given the recent advancements in technology, a new domain known as electronic sports (esports) has emerged. As human-computer interaction mediates esports performance, the virtual nature of esports may not be affected to the same extent by the limitations of previous expertise research. Therefore, this leading article argues that esports provides an excellent opportunity to further advance research on the development and assessment of human expertise.

What is esports?

Esports involves individuals and/or teams of players who compete in video game competitions via human-computer interaction. Participation in esports has increased substantially over the past decade, with an estimated population over 100 million players worldwide. To date, esports research has primarily focused on the factors that influence participation (Braun, Stopfer, Müller, Beutel, & Egloff, 2016; Griffiths, Davies, & Chappell, 2003; Seo, 2016). Although information about player engagement is becoming clear, a scarce amount of research has investigated the factors that underlie expertise in esports. Esports consists of several categories, some of which include multiplayer online battle arena, multiplayer online role-playing, real-time strategy, and first-person shooter games. A common theme among these categories is that performance is typically carried out in a team-based environment, where a player's avatar is placed in a virtual environment with the goal of eliminating their competitors or achieve an objective (e.g. capture the flag). A player combines their perceptual-cognitive abilities (e.g. anticipation, visual search behaviour, pattern recall and decision-making) and domain-specific skills (e.g. keyboard and mouse movements) to achieve successful performance. Given human-computer interaction mediates esports performance, there are many inherent advantages for expertise research. Firstly, developmental activities are objectively tracked and automatically logged online. Secondly, the constraints of a laboratory setting correspond with a real-world environment of esports performance. Thirdly, as esports has emerged recently, expertise is yet to be confounded by the influence of guided systematic training environments. Therefore, the following subsections discusses these advantages that esports performance offers to researchers in the expertise field.

The developmental activities related to expertise

A prominent area of expertise research is aimed towards understanding how practice can lead to the attainment of expertise (Côté et al., 2007; Ericsson, 2014; Ward et al., 2007). Accurately mapping an individual's practice history can elicit key insights about developmental milestones (Côté & Abernethy, 2012; Ford & Williams, 2012). Qualitative interviews, training study questionnaires and diary reports are commonly used methods to establish a practice history profile (Baker et al., 2003; Côté & Abernethy, 2012; Memmert, Baker, & Bertsch, 2010). Across these methods, participants retrospectively recall their practice activities over their career. Given careers can span many years, careful interpretation is recommended when analysing the information (Howard, 2011). However, this approach is influenced by an individual's recall bias and memory recall ability. Participants generally overestimate the number of practice hours and time since recent milestones and underestimate the number of practice hours and the time since distant ones, often referred to as the telescoping effect (Howard, 2011; Kemp, 1988). This effect can compromise the validity and reliability of data collected using retrospective recall.

Longitudinal follow-up studies are a valuable alternative compared with retrospective recall. However, longitudinal data collection on human behaviour can be expensive, time consuming and requires a large sample size because of poor participant retention (Patel et al., 2003). Despite the clear strengths of the design, this creates difficulties when developing practice history profiles that accurately reflect the trajectory of development. Comparatively, esports software records practice activities online which may provide a suitable medium to further explore the relationship between developmental activities and expertise. Both the quantity (e.g. total hours played, matches played, etc.) and quality of performance (e.g. outcome of match, player rating, performance rank, etc.) are automatically logged on online servers that are freely available to the public. The public repositories can establish a practice history profile, which can be updated to follow a player's developmental trajectory throughout their career. Profiling can be performed for all skill levels of esports players, which is useful for tracking across a developmental spectrum rather than just from a dichotomous viewpoint (e.g. elite vs non-elite) (Swann, Moran, & Piggott, 2015). Another example is tracking a players and/or teams practice activity throughout a competitive season. Researchers can examine the contribution that different practice activities have on performance. Information gained from this approach can inform coaches and practitioners with developing effective training strategies when preparing for competition. Using this approach reduces the logistical demands on data collection and data analysis, making it a cost effective and time efficient method of analysing an individual's career trajectory. Another advantage is that the influence of individual recall bias is negated, which improves the validity and reliability of the specific performance outcome measures of interest. While much of the data is publicly available, researchers must ensure that they comply with the legislations, rules and policies of their institution's ethics committee and national regulations. If the data is obtained through a third-party repository, it must comply to the original data licensing structure. Further consideration is required for aspiring players under the age of 18, as their publicly available data will be collected when they are a minor. However, the minimum age requirement to participate in a prized pool tournament is 18 years of age. Lastly, in most cases players have the option to list their online profile as private to prevent access to their personal data. As such, the complex and sensitive nature of this method must be conveyed to the appropriate ethics committee for review. Collectively, esports provides a platform to quantify the developmental activities related to expertise without the limitations associated with long-term follow up studies that rely on retrospective recall.

The development of ecologically valid tasks

A key area of expertise research is developing tasks that provide accurate and reproducible measurements that can be objectively evaluated in a controlled laboratory setting (Mann et al., 2007; Williams et al., 2011). Many studies in controlled laboratory settings use a form of technology to simulate the constraints of a real-world environment of the domain in question (Savelsbergh et al., 2002; Williams & Ericsson, 2005). However, concerns have been raised about whether such tasks indirectly measure a related function or ability rather than the specific and complex mechanisms that mediate expert performance (Hadlow, Panchuk, Mann, Portus, & Abernethy, 2018; Williams & Ericsson, 2005). Over time researchers have continued to improve the ecologically validity of task-representative designs to closely resemble the dynamic and ever-changing nature of a real-world environment (Burgess et al., 2006; Mann et al., 2007; Williams & Ericsson, 2005). Research studies aimed at quantifying expert performance often trade-off external validity for the internal validity of a task, and vice versa. Evidentially, it remains difficult to develop task representative designs that allow participants to (re)produce the behaviours observed in a real-world environment while maximizing the control that can be exerted over a task.

As human-computer interaction mediates esports performance, it may provide the ideal platform to investigate expertise as task representative designs resemble a real-world environment, without sacrificing internal validity. Traditional task representative designs have used technology (e.g. television screens, computer monitors and video projector screens) with simulated responses (e.g. pressing a button or key and moving a joystick or mouse) (Hadlow et al., 2018). Despite being highly controllable, the implementation of this method instead of more externally valid tasks will inadvertently alter the perception-action coupling of a real-world environment (Kay & Kelso, 2016). However, as esports is mediated by this form of technology for both competition and training, the perception-action coupling experienced during performance can be accurately replicated in a controlled laboratory setting. Researchers can customise in-built settings within the software used in esports to develop highly controlled training interventions without sacrificing task representativeness. An example of this is assessing a range of performance-related characteristics, such as fine-motor coordination, processing ability and decision-making. Assessing a range of performance-related characteristics can highlight differences between esports categories where certain characteristics may be more necessary than others. Certain esports (e.g. League of Legends) have regular in-game changes to address game balance issues or provide new content for players. Therefore, the authors propose that researchers should state the current version of the game and provide a reference to the rules at that point of time whenever possible. In rare circumstances that major rule changes occur, these differences should be stated explicitly in-text when discussing esports studies together. Furthermore, an esports player's behavioural response can be measured through the available hardware (e.g. keyboard and mouse responses). Esports with a clear and measurable performance outcome are more suited for performance-related research. Examples where researchers and practitioners can objectively examine a player's performance include the HLTV rating for Counter-Strike: Global Offensive and the Kill/Death/Assist ratio for League of Legends. In terms of learning-related research, esports that allow researchers and practitioners to develop online training scenarios are more suitable. Examples where researchers and practitioners can create their own training interventions within a realistic environment include the authoring tool for Counter-Strike: Global Offensive and the practice tool for League of Legends. Hence, the virtual nature of esports performance can translate a real-world environment within a controlled laboratory setting under standardised conditions.

The confounding factors that influence expertise

The developmental process of systematically developed expertise reflects the dynamic interaction between natural abilities, intrapersonal skills and environmental factors (Ericsson et al., 2009; Gagné, 2004, 2009). Furthermore, catalysts (i.e. intrapersonal, environmental and chance) can either assist or hinder the developmental process (Gagné, 2004). A commonly reported catalyst that confounds the development of expertise is the influence of a guided systematic training environment (Barab & Plucker, 2002; Burgess & Naughton, 2010). Within traditional domains of expertise, individuals who demonstrate an aptitude are identified at an early age and selected to undergo a structured development program. A structured development program is a commonplace in music (i.e. music academies and conservatories), sport (i.e. sports schools and talent development programs), and education (i.e. selective schools for gifted and talented students). These programs provide individuals with high-quality resources (e.g. support staff, specialised coaching, and logistical support) to develop their natural abilities into talents, with the goal of developing excellence (Côté & Abernethy, 2012). As such, the development of expertise is confounded by the practices implemented across the many guided systematic training environments that exist (Baker et al., 2003). However, the effect a guided systematic training environment has on the development of expertise is difficult to quantify. Therefore, investigating expertise in a domain that has been exposed to these confounders to a lesser extent could provide an opportunity into the development of expertise outside of the constraints of guided systematic training environments.

There are many confounders in traditional domains of expertise, such as maturational factors, the role of coach, support from significant others and cultural factors, among others (Baker & Horton, 2004; Baker et al., 2003). The interaction between these factors underlies the likelihood of developing expertise, which is largely determined by the access to a guided systematic training environment (Baker et al., 2003). However, the emergence of esports professionalism has only recently sparked the development of specialised high-performance centres and support staff focused on developing excellence. Therefore, the existing pool of expert esports players have emerged largely without guided systematic training environments. As the professionalism of esports continues to increase, the access to publicly available data of high-level teams is becoming less accessible. Therefore, the authors encourage esports to follow traditional monitoring approaches by embedding researchers within professional teams to collect data at the highest level of competition. Additionally, the growing population of esports players offers a wealth of information about the interaction of natural abilities and intrapersonal skills. Therefore, esports is a domain that is more likely to reflect an individual's raw abilities and skills as it is yet to be tainted by many of the confounders that complicate our understanding about the development of expertise.

Conclusion

The purpose of this leading article was to provide rationale for why esports is the ideal domain for those with an interest in the assessment and development of human expertise. Three key advantages of applying the expert performance approach in esports were discussed in this article: i) developmental activities are objectively tracked and automatically logged online, which can be used for a detailed report on a player's developmental trajectory ii) the constraints of representative tasks correspond with the real-world environment of esports performance, which translates a real-world environment within a controlled laboratory setting under standardised conditions, and iii) expertise has emerged without the influence of guided systematic training environments, which presents an opportunity to investigate in a domain yet to be tainted by many of the confounders that complicate our understanding about the development of expertise. As such, esports provides a window for researchers to further improve their understanding about the assessment and development of human expertise in the modern world. Therefore, the authors recommend embracing this emerging area as it may have the answers to many of the future recommendations that the expertise field continues to seek.

Chapter 4:

Study 2

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 with 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 ($p < 0.001$, $\eta_p^2 = 0.35$). Significant univariate effects were identified on the movement time ($p = < 0.001$, $\eta_p^2 = 0.42$), two-choice response time ($p = 0.038$, $\eta_p^2 = 0.09$), congruent precue response time ($p = 0.010$, $\eta_p^2 = 0.12$) and incongruent precue response time ($p = 0.047$, $\eta_p^2 = 0.08$). 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 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 et al., 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 et al., 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 et al., 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 et al., 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 et al., 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: (i) professional (age: 22.05 ± 3.18 y, sex: male = 25, female = 0), (ii) recreational (age: 25.80 ± 4.93 y, sex: male = 21, female = 4), and (iii) 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 standardised 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 standardised conditions. Group-wise differences were examined through multivariate and univariate analysis of variance.

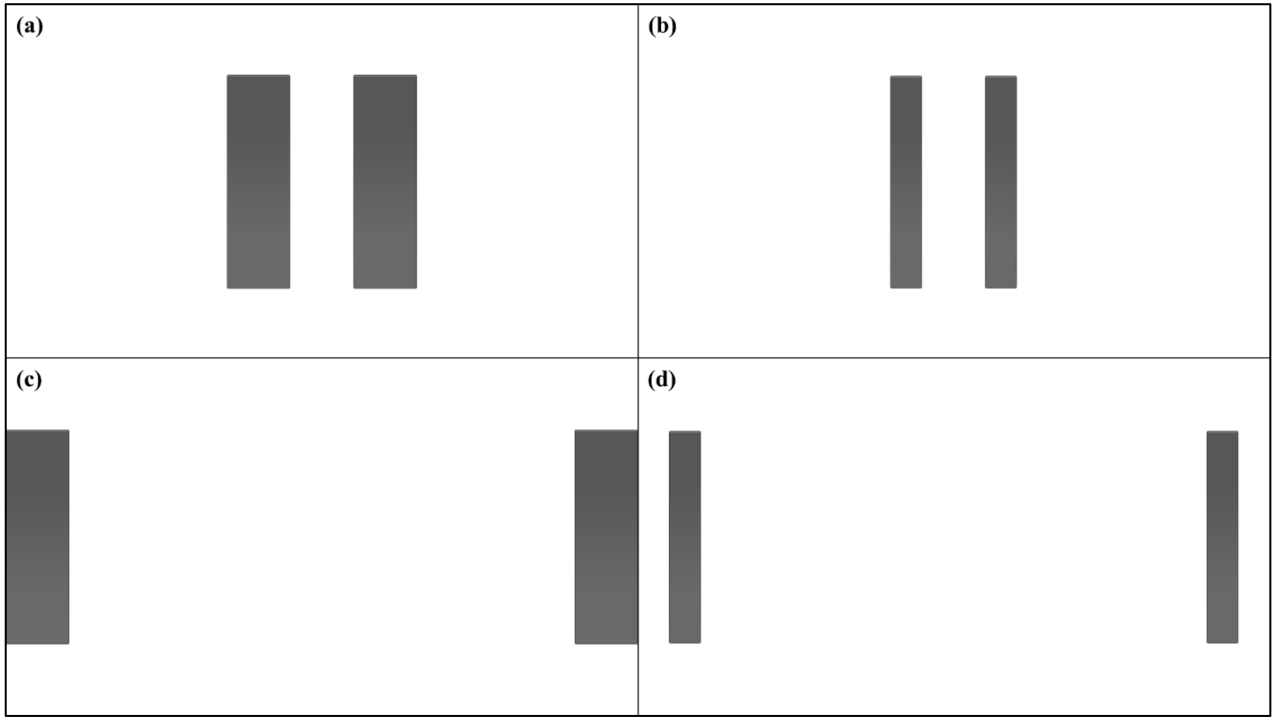
Manual dexterity

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. Lastly, 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 rapidly switch between targets while minimising movement errors was assessed using an adapted computer-based clicking task (Fitts, 1954), which was developed using Unity software (Unity, Version 2018.3, 2018). 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 increases, a greater movement time for execution is required. 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. 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 standardised 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 familiarise themselves with the equipment and standardised mouse settings. Participants completed all trials in a randomised order. 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)

Figure 4.1. 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).



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 customised, four-button controller. All response time tasks were developed using Unity software (Unity, Version 2018.3, 2018). Participants received standardised 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 randomised 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 centralised 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 were 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 familiarise themselves with the equipment. Participants completed all trials in a randomised 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 analysed according to their accuracy after data collection. For the response time tasks, responses that did not correspond with the stimulus circle were labelled 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 labelling rule was used. The labelling 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 25th and 75th percentiles $\pm$ 1.5 $\times$ IQR were considered outliers and discarded (Hoaglin & Iglewicz, 1987; Hoaglin, Iglewicz, & Tukey, 1986). A total of 53 out of 7,200 trials were labelled 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 $\pm$ standard deviation. Preliminary analysis using a univariate analysis of variance was undertaken to determine the potential confounding effect of age. One multivariate analysis of variance 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 (ms), two-choice response time (ms), four-choice response time (ms), congruent precue response time (ms) and incongruent precue response time (ms). 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 $p < 0.05$. 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 4.1 displays the mean ± standard deviation for all data. A multivariate effect of expertise group on performance characteristics was identified ($p < 0.001$, $\eta_p^2 = 0.35$). 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 ($p = < 0.001$, $\eta_p^2 = 0.42$). 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 ($p = < 0.038$,

$\eta^2_p = 0.09$), faster congruent precue response times ($p = < 0.010$, $\eta^2_p = 0.09$), and faster incongruent precue response times ($p = < 0.047$, $\eta^2_p = 0.08$) compared with the control group, but not with recreational esports players.

Table 4.1. 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^{a}	523.51 ± 60.11^{b}	481.73 ± 76.19^{b}	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^{a}	325 ± 4.06^{a,b}	318 ± 3.21^{b}	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^{a}	356 ± 5.10^{a,b}	345 ± 4.90^{b}	4.92*	0.12
Incongruent response time (ms)	432 ± 5.44^{a}	410 ± 4.83^{a,b}	395 ± 5.15^{b}	3.19*	0.08

*Note: * = p < 0.05, ** = p < 0.01, ^{a} = significant univariate effect (p < 0.05), ^{b} = significant multivariate effect (p <0.05).*

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 shorter 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 et al. (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 shorter 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 shorter 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. Firstly, standardised 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. Secondly, 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 minimise the influence this may have, participants received were encouraged to only proceed if they were comfortable to perform the task.

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.

Chapter 5:

Study 3

Exploring fitts' law: the speed-accuracy trade-off in esports

Pluss, M.A., Novak, A. R., Bennett, K. J. M., Panchuk, D., Coutts, A., & Fransen, J. (Prepared for submission). Exploring fitts' law: the speed-accuracy trade-off in esports.

Abstract

The current study aimed to explore Fitts' law with a computerised speed-accuracy trade-off task in 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 with their expertise level (i.e. professional: n = 25, recreational: n = 25 and control: n = 25). The movement time and accuracy of eight different indices of difficulty were assessed in a randomised order. Group-wise differences were examined through multivariate and univariate analysis of variance. A significant moderate ID*group interaction effect was identified for movement time ($F_{(11,399)} = 2.245$, $p = 0.012$, $\eta_p^2 = 0.06$). Furthermore, significant strong main effects were also identified for group ($F_{(2,72)} = 25.461$, $p < 0.001$, $\eta_p^2 = 0.41$) and movement time ($F_{(6,399)} = 556.6$, $p < 0.001$, $\eta_p^2 = 0.89$). Overall, the professional group displayed significantly shorter movement times and are also more likely to adapt their movement time to changes in task difficulty with imposed accuracy demands when compared with the recreational group and the control group. Based on this study's findings, there is a clear need for future research to understand the distribution of responses and the strategies adopted by esports players of different expertise levels within a computerised speed-accuracy trade-off task.

Keywords: electronic sports, expert performance, excellence, skilled performance, video games, gaming

Introduction

When executing any type of movement, there is typically a trade-off between the speed with which the movement is performed and the degree of accuracy with which the movement is made (Beilock et al., 2008; Dean, Wu, & Maloney, 2007; Plamondon & Alimi, 1997). In daily situations, such as typing on a keyboard, many motor tasks require the individual to perform with high accuracy at high speed, in the sense that the task rewards both speed and accuracy (Beilock, Bertenthal, McCoy, & Carr, 2004; Dane & Pratt, 2007; Dean et al., 2007; Tsang, 1998). In such contexts, the individual needs to consider whether if they move too fast, they will gain an advantage in speed but at the cost of poorer accuracy. Alternatively, if they slow down their movements, they will achieve higher accuracy but with a loss of speed (Chittka, Skorupski, & Raine, 2009; Heitz, 2014). Although strategies used in speed-accuracy tasks may vary on the task at hand, performance in speed-accuracy tasks has often distinguished between expertise level (Beilock et al., 2008; García, Menayo, & Del Val, 2017). For example, in domains such as medicine and sport, experts demonstrate a shorter movement time and are be better at adapting their movement time to changes in task difficulty with imposed accuracy demands in tasks examining the speed-accuracy trade-off when compared with novices (Beilock et al., 2004; Suebnukarn, Phatthanasathiankul, Sombatweroje, Rhienmora, & Haddawy, 2009; van den Tillaar & Ettema, 2006).

Fitts' law (the time required to rapidly move to a target area is a function of the ratio between the distance to the target and the width of the target) has served as one of the few quantitative foundations for human-computer interaction research (Zhai et al., 2004). While Fitts' law has been examined primarily in simple motor tasks (e.g. reaching for a target), less is known about Fitts' law in complex motor tasks (e.g. rapidly and accurately executing repetitive movements) (Langolf, Chaffin, & Foulke, 1976; Smits-Engelsman, Van Galen, & Duysens, 2002). Typically, there are difficulties with exploring Fitts' law in more complex tasks because researchers are often faced with a trade-off between higher degrees of experimental control (i.e. laboratory settings) for less replication of performance (i.e. field settings), or vice versa when developing representative tasks (Gillan, Holden, Adam, Rudisill, & Magee, 1992; Langolf et al., 1976). Overall, it is a challenge for researchers to develop tasks with high external validity, whereby the task accurately describes and measures performance under specific task constraints that effectively capture the functional responses of performers in representative situations (Ericsson & Lehmann, 1996; Helsen & Starkes, 1999; Williams & Ericsson, 2005). Therefore, future research would benefit from exploring Fitts' law in a domain where the constraints of representative tasks closely resemble a real-world environment.

During human-computer interaction tasks, people send inputs to computers through pointing devices (e.g. mouse, touchpad, and track point) and receive outputs on visual displays (e.g. computer monitor). As human-computer interaction mediates electronic sports (esports) performance, it is worthwhile to explore Fitts' Law in a domain with high external validity (Pluss et al., 2019). Esports involve individuals or teams of players who compete in video game competitions through human-computer interaction (Pluss et al., 2019). As such, the context in which esports players perform (i.e. the ability to accurately move and click the mouse to perform their intended action) offers researchers the opportunity to develop assessment tasks that closely mimic the movements of competition within a laboratory setting with high external validity (Campbell et al., 2018; Dale & Green, 2017; Pedraza-Ramirez et al., 2020; Pluss et al., 2019; Pluss et al., 2020). Therefore, the current study aimed to explore Fitts' law in esports players using an expert/nonexpert paradigm. Following previous expertise research, it was hypothesised that professional esports players would display significantly shorter movement times when compared with recreational esports players and a control group in a speed-accuracy trade-off assessment (Beilock et al., 2008; Beilock et al., 2004). Furthermore, it was hypothesised that professional esports players will be better at adapting their movement time to changes in task difficulty with imposed accuracy demands when compared with recreational esports players and a control group (Beilock et al., 2008; Beilock et al., 2004).

Methods

Participants

Data were collected from 75 participants (age: 24.2 ± 4.2 y, sex: male = 64, female = 11) who volunteered to participate in the current study. Participants were *a priori* classified into three expertise groups: (i) professional (age: 22.1 ± 3.2 y, sex: male = 25, female = 0), (ii) recreational (age: 25.8 ± 4.9 y, sex: male = 21, female = 4), and (iii) control (age: 24.7 ± 3.8 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 had full-time contracts (a minimum of 38 hours of scheduled training per week) with 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 individuals who play video games 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 of 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 video gaming. 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

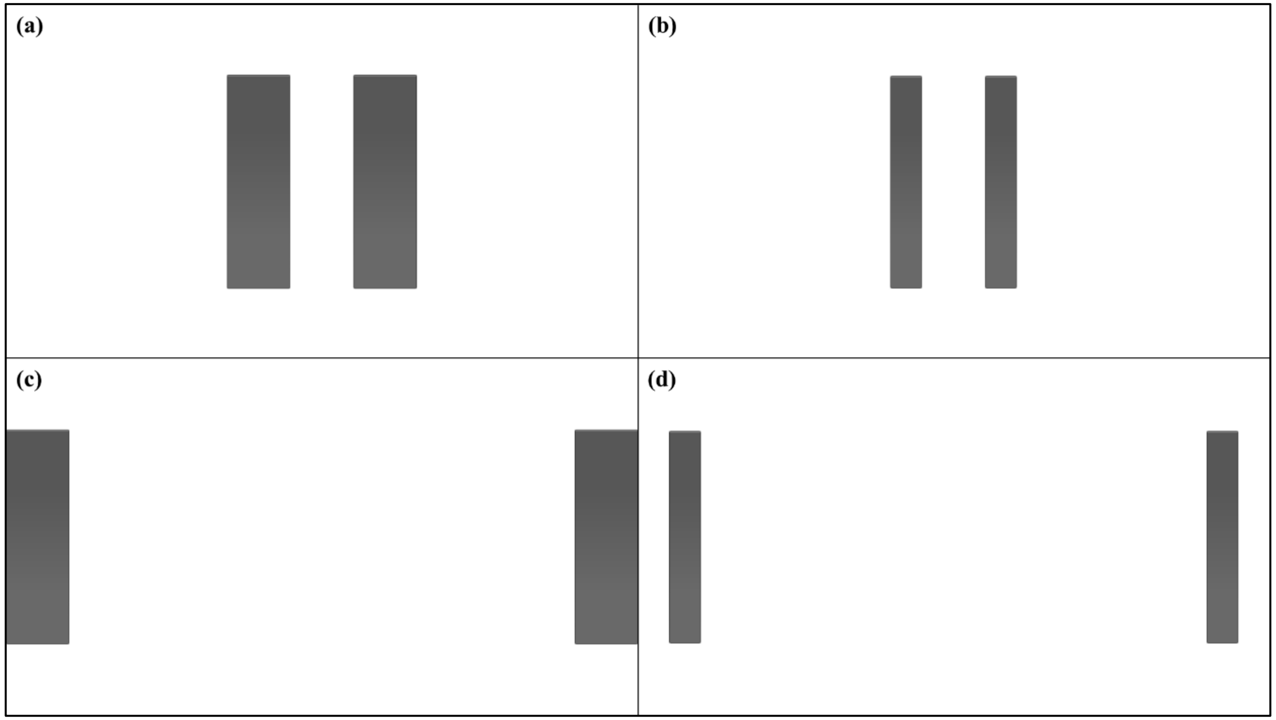
The data in the present study is a subsample of the speed-accuracy trade-off data collected from a multifactorial assessment (e.g. manual dexterity, speed-accuracy trade-off, and a variety of response times) of perceptual-motor abilities of esports players (Pluss et al., 2020). Given that performance in the speed-accuracy trade-off was the main distinguishing factor between the level of expertise, a more detailed analysis was warranted. Therefore, the study followed a cross-sectional study design to examine Fitts' law in esports players of three different expertise levels (professional, recreational and control). The order that participants completed all of the eight different indices of difficulty were randomised (using a random number generator). Assessing a range of different IDs allows for a comprehensive understanding about the time required to rapidly move to a target area as a function between the distance to the target and the width of the target (MacKenzie, 1992). All assessments were conducted in a laboratory setting under standardised conditions (a well-lit quiet room). Group-wise differences were examined through multivariate and univariate analysis of variance.

Speed-accuracy trade-off task

The ability to rapidly switch between targets while minimising movement errors was assessed using a computer-based tapping task adapted from the original tapping task developed by Fitts (1954). The computerised task used in this study was developed using Unity software (Unity, Version 2018.3, 2018). According to Fitts' law, human movement can be modelled by analogy to the transmission of information (Fitts, 1954). Fitts' law states that the log-linear relationship between the amplitude (A) of the movement (also referred to as the distance to a target), the target width (W), and the mean movement time (MT), is given by the following equation: $\mathrm{MT} = a + b\,[\log_2(2A/W)]$. In spatially constrained movements where both A and W are given, $2A/W$ is related to the number of possible movements, and the $\log_2$ is the information required (in bits) to resolve the uncertainty among them. As the amount of information that can be processed per unit of time is limited, a person has to adapt to a difficult combination of A and W by increasing the movement time or by becoming less accurate. The difficulty of the movement is represented by the value $\log_2 (2A/W)$ and is called the index of difficulty (ID). The amount of information that humans can process per unit of time is called the index of performance (IP) and is represented by the ratio of ID (in bits) over movement time (in seconds). Overall, it is widely documented that movement time increases linearly with the logarithm of $2A/W$ and thus linearly with the ID (Heitz, 2014; Smits-Engelsman et al., 2002). Therefore, to evaluate the speed-accuracy trade-off, eight different indices of difficulty were assessed (ID 1, ID 2^A, ID 2^B, ID 3^A, ID 3^B, ID 4^A, ID 4^B, ID 5). If an index of difficulty had a ^{B} superscript, the distance between the targets remained the same, however the width of the targets was half the size of the ^{A} superscript option. The task was displayed on a digital screen (16:9 aspect ratio with a 1920 x 1080 resolution) and performed with a Razer Naga wired mouse (Razer, San Diego, California, USA) set at a cursor speed of 800 dots per inch.

Participants received standardised 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 familiarise themselves with the equipment and standardised mouse settings. Participants completed all trials in a randomised order. Contrary to Fitts (1954) original manual aiming task, a minimum of 90% accuracy was required for a successful trial. This allows researchers to emphasise accuracy, which is more representative of the actions displayed by esports players in competition. If 90% accuracy was not achieved, participants repeated the same trial until a successful trial was achieved (on average there was 2.81 ± 3.76 unsuccessful trials per participant). The accuracy of a trial was an automatic function developed within the customised software and was displayed at the end of each attempt. After a three-second countdown, the participant commenced a trial. After 10 seconds, 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). Given that a minimum of 90% accuracy was required for a successful trial, only movement time (ms) was retained as a dependent variable for statistical analysis. The accuracy values for each group include professional (97.05 ± 3.17%), recreational (96.86 ± 3.48%) and control (97.07 ± 2.88%).

Figure 5.1. A visual depiction of different index of difficulties within the speed-accuracy trade-off task. Examples depicted are: ID 2^A (a), ID 2^B (b), ID 4^A (c), ID 4^B (d).



Statistical analysis

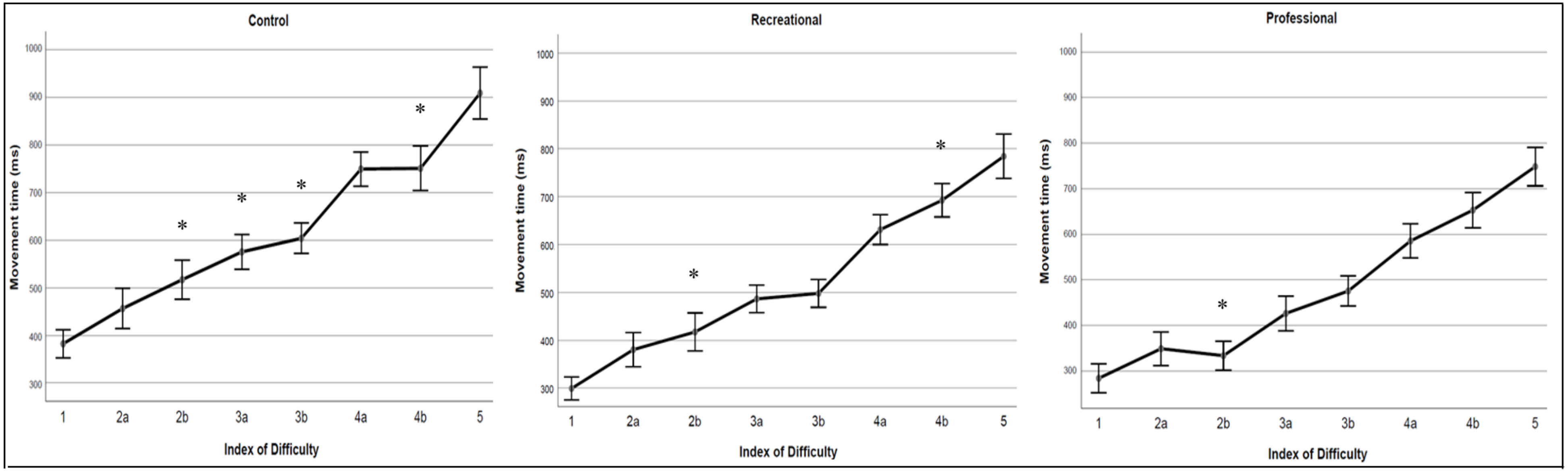
Assumptions of normality were assessed using a Shapiro-Wilk test and visual inspection of the frequency distribution for all dependent variables. Additionally, homogeneity of variance at the within and between-subjects level was explored using Mauchly's Test of sphericity and Levene's tests. Descriptive statistics were calculated for all variables and presented as mean ± standard deviation (SD). Preliminary analysis using a univariate analysis of variance was undertaken to determine the potential confounding effect of age. A repeated measures ANOVA was used to investigate the differences in means of the dependent variables (movement time) between levels of the fixed factor (expertise level) across the different indices of difficulty (within-subjects variable). Furthermore, both linear and non-linear relationships were explored within the repeated measures ANOVA. Bonferroni *post-hoc* corrections were applied to allow for multiple comparisons and to determine individual differences between each paired level within the fixed factor. In addition, a split file was used to obtain three separate repeated measures ANOVAs for each group allowed for pairwise comparisons, which further improved the understanding about the relationship between the movement time and ID for each group. A criterion alpha level significance was set at $p < 0.05$. 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

Age was not a significant confounding variable in the relationship between performance on the speed-accuracy trade-off task and expertise level (age main effect: $F_{(1,71)} = 0.487$, $p = 0.487$, $\eta_p^2 = 0.01$, ID*age interaction effect: $F_{(7,65)} = 1.015$, $p = 0.429$, $\eta_p^2 = 0.10$). As such, subsequent analyses did not control for age as a covariate. While no between-group heterogeneity of variance was observed (Levene's tests: $p > 0.05$), within-subjects heterogeneity of variance was apparent (Mauchly's Test of sphericity: $W = 0.368$, $p < 0.001$). Therefore, Greenhouse-Geisser corrections were applied for the interpretation of the multivariate and univariate effects where appropriate. A significant moderate ID*group interaction effect was identified for movement time ($F_{(11,399)} = 2.245$, $p = 0.012$, $\eta_p^2 = 0.06$). Furthermore, significant strong main effects were also identified for group ($F_{(2,72)} = 25.461$, $p < 0.001$, $\eta_p^2 = 0.41$) and movement time ($F_{(6,399)} = 556.6$, $p < 0.001$, $\eta_p^2 = 0.89$). Independent of expertise level, the relationship between ID and movement time was best described using a linear ($p < 0.001$, $\eta_p^2 = 0.98$) or quadratic ($p < 0.001$, $\eta_p^2 = 0.50$) relationship. However, the ID*group interaction effect was best described using a cubic regression ($p = 0.035$, $\eta_p^2 = 0.09$) or 6th order polynomial ($p = 0.004$, $\eta_p^2 = 0.15$). The control groups' movement time was significantly ($p < 0.001$) slower across all IDs when compared with the recreational group (Δ movement time between control-recreational = 94.6 ms [46.6 – 142.6]) and the professional group (Δ movement time between control-professional = 136.4 ms [88.4 – 184.3]). However, no significant differences ($p > 0.05$) were observed between the recreational group and the professional group (41.8 ms [-6.2 – 89.8]). Independent of expertise level, there were significant differences in movement time between all IDs ($p < 0.05$), except for ID 2^A and ID 2^B ($p = 0.270$) and ID 3^A and ID 3^B ($p = 0.058$). When analysing the output of the model by groups, in the control group, mean movement times were significantly different ($p < 0.05$) between all IDs, except ID 2^A and ID 2^B ($p = 0.225$), ID 2^B and ID 3^A ($p = 0.423$), ID 3^A and ID 3^B ($p = 1.000$), and ID 4^A and ID 4^B ($p = 1.000$). The relationship between ID and movement time in the control group was best described by a linear ($p < 0.001$, $\eta_p^2 = 0.89$) or quadratic ($p = 0.008$, $\eta_p^2 = 0.26$) relationship. In the recreational group, mean movement times were significantly different ($p < 0.05$) between all IDs except between

ID 2^A and ID 2^B ($p = 1.000$), and ID 4^A and ID 4^B ($p = 0.152$). The relationship between ID and movement time in the recreational group was best described by a linear ($p < 0.001$, $\eta_p^2 = 0.98$) or quadratic relationship ($p < 0.001$, $\eta_p^2 = 0.53$) relationship. In the professional group, mean movement times were significantly different ($p < 0.05$) between all IDs except between ID 2^A and ID 2^B ($p = 1.000$). The relationship between ID and movement time in the professional group was best described by a linear ($p < 0.001$, $\eta_p^2 = 0.98$) or quadratic ($p < 0.001$, $\eta_p^2 = 0.75$) relationship.

Figure 5.2. Mean movement time (ms) with 95% confidence intervals for different indices of difficulty for the control, recreational, and professional groups.



Note: * = demonstrates that movement time was not significantly different from the previous ID (p > 0.05).

Discussion

The current study aimed to explore Fitts' Law in a computerised speed-accuracy trade-off task adapted from the original Fitts' (1954) tapping task in three different *a priori* classified esports expertise levels (e.g. professional, recreational and control). The findings of the present study correspond with Fitts' law, which indicates a linear relationship between movement time and $\log_2$ ($2A/W$). Although movement time increased linearly with the ID for each group, the professional esports players displayed the shortest movement times for each ID when compared with the recreational group and control group. There were minimal significant differences between the conditions where the distance between the targets remained the same, but the width of the targets was half the size in the recreational (only ID 3^A and ID 3^B) and control (no significant differences) groups. However, there were several significant differences in mean movement time between the conditions where the distance between the targets remained the same, but the width of the targets decreased by half for the professional group (except for ID 2^A and ^{B}).

In line with similar work, group-wise differences in movement time were identified between experienced video game players and individuals with no video game experience (Kowal et al., 2018; McDermott, Bavelier, & Green, 2014). Kowal et al. (2018) reported experienced video game players adopt a strategy that favours speed over accuracy in a task-switching assessment when compared with individuals with little to no video game experience. Furthermore, McDermott et al. (2014) documented that action video game players displayed significantly greater speed but suffer a marginal loss in accuracy in a task that measures response inhibition when compared with non-action video game players. Overall, these findings support that in manual aiming skills, experts demonstrate shorter movement times when tasks constraints are imposed on performance when compared with novices (Proteau, 1992; Proteau & Marteniuk, 1993; Proteau et al., 1992).

Groupwise comparisons of movement time provide an insight into the trends associated with the relationship between ID and movement time. Certain trends (i.e. linear and quadratic relationships) associated with the ID and movement time differed for each group. While the effect sizes associated with a linear relationship between movement time and ID were similar for each group, the effect sizes associated with a quadratic relationship between movement time and ID were strongest in the professional group. Evidentially, the relationship between ID and movement time changes more rapidly once the ID of a task reaches a threshold, which in the case of the current study was between ID 3^{B} to ID 4^{A}. After this threshold has been exceeded, it appears that the movement of the professional group changes more rapidly when compared with the recreational group and the control group. This may reflect that with certain accuracy demands, professional esports players are more sensitive to changes in conditions after the ID has exceeded a certain threshold.

Anecdotally, a common characteristic in first-person shooters (e.g. Counter-strike: Global Offensive, Overwatch, and PUBG), and multiplayer online battle arenas (e.g. League of Legends and Heroes of the Storm) esports players is that they typically maintain the position of the cursor in areas of relative importance (e.g. likelihood of areas where the opponent may appear) as it will likely result in more successful outcomes of performance (e.g. winning the objective, eliminating the opposition). Given the position of the cursor is close to the areas of importance, there are several benefits this may have on performance: i) there is less distance to move when a stimulus appears, which likely decreases the likelihood of movement errors, ii) it allows the ability to prepare the action when required iii) reduces the potential influence of the speed-accuracy trade-off. Perhaps this is a potential explanation as to why the movement time of the professional group was slower when the imposed accuracy demands increased. It is likely that lower IDs reflect the movements that would typically characterise esports performance, whereas the higher

IDs reflect the movements that would be observed in rare instances were an esports player has not maintained the position of their cursor in areas of relative importance. Given higher IDs reflect the movements that typically would not characterise esports performance, these findings support other research that suggests that experts will outperform novices in tasks they are familiar with, however performance differences are less likely to be evident in tasks that do not accurately replicate the behavioural characteristics that would be observed in performance (Adams et al., 2013; Seamster et al., 2000)

Inherently, there are limitations present within the current study. Firstly, standardised equipment (i.e. mouse) and settings (i.e. dots per inch) were employed. While standardising the equipment and settings increases the control over the study design, it is possible that esports players performing the speed-accuracy task with a different mouse and sensitivity (compared with their own personal settings) 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. Secondly, is the possibility of fatigue or other testing conditions (i.e. participants may gradually improve or decline due to factors in the testing environment) may have on performance. To minimise the influence this may have on performance, participants were encouraged to only proceed if they were comfortable to perform the task.

Conclusion

The current study aimed to explore Fitts' law in esports players with an expert/nonexpert paradigm. Overall, there was a general trend towards an increase in movement time as the index of difficulty increased across all groups. In addition, professional esports players displayed significantly shorter movement times when compared with recreational esports players and the control group. However, professional esports players were more susceptible to the speed-accuracy trade-off when compared with recreational esports players and the control group. Based on this study's findings, there is a clear need for future research to understand the distribution of responses and the strategies adopted by esports players of different expertise levels within a computerised speed-accuracy trade-off task.

Acknowledgements

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

Disclosure statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that would be construed as a potential conflict of interest.

Chapter 6:

Study 4

Assessing the reliability and validity of an esports perceptual-motor skill assessment

Pluss, M.A., Novak, A. R., Bennett, K. J. M., Panchuk, D., Coutts, A., & Fransen, J. (Prepared for submission). The reliability and validity of an esports perceptual-motor skill assessment.

Abstract

The aim of this study was to investigate the test-retest reliability and construct validity and of an esports perceptual-motor skill assessment. Forty participants (age: 24.15 ± 3.68 y, sex: male = 31, female = 9) were a priori classified into two expertise groups: (1) esports players (age: 22.98 ± 3.64 y, sex: male = 18, female = 2), and (2) controls (age: 25.31 ± 3.42 y, sex: male = 13, female = 7). Following a familiarisation period, participants completed three separate trials of a commonly used esports perceptual-motor skill assessment (Mobalytics Proving Ground Test). To assess test-retest reliability, variables displaying normal distributions were analysed using intraclass correlation coefficient (ICC) estimates for two-way mixed effects models with 95% confidence intervals. The average ICC for all the independent variables in the control group and esports groups were moderate (ICC control = 0.72 and ICC esports = 0.53). The average 95% confidence intervals for the independent variables in the control group was ICC = 0.55 – 0.86 and ICC = 0.30 – 0.75 in the esports group. When analysing the results of the Friedman test, the average effect size for the independent variables was 0.07 and 0.11 in the control and esports groups, respectively. In terms of construct validity, there were significant differences ($p < 0.0017$) for 17 variables when comparing the best scores of each group. Overall, the esports perceptual-motor skill assessment used in the current study can to some extent discriminate between an esports player and a control group.

Keywords: electronic sports, expert performance, excellence, skilled performance, video games

Introduction

Electronic sports (esports) – sport-based competitions using video games – is a dynamic and evolving area of expertise research that is receiving considerable attention from the sports science and psychology disciplines (Bányai et al., 2019; Pedraza-Ramirez et al., 2020; Pluss et al., 2019). In its simplest form, esports involve individuals or teams of players who compete in video game competitions through human-computer interaction (Pluss et al., 2019). Esports players seemingly integrate a range of perceptual-cognitive skills and perceptual-motor abilities to produce goal-directed movements in a dynamic environment (Pluss et al., 2020). However, esports has only recently received interest from researchers, which is why there is limited research that details the perceptual-motor skills of esports players or which assessments are appropriate to measure such skills (Pluss et al., 2020). In other domains of expertise, researchers and coaches typically implement both objective and subjective assessments to quantify players performance characteristics (Haycraft, Kovalchik, Pyne, & Robertson, 2017; McIntosh, Kovalchik, & Robertson, 2019). However, given the recent emergence of esports, a significant limitation associated with existing assessment and training tools (e.g. Mobalytics Proving Ground Test, OSU, 3D Aim Trainer, and Aim lab) is the lack of data about the validity and reliability of the assessment. As a result, it is difficult to determine whether the assessment is measuring what it claims to measure. Therefore, it is warranted that future research examines the reliability and validity of an esports perceptual-motor skill assessment.

Anecdotally, perceptual-cognitive skills (e.g. mechanics, background processing and map awareness) are integral to a player's ability to make decisions and execute esports-specific actions during competition. During competition, players perceive and interpret environmental information (e.g. the positioning of their virtual avatar, their teammates, and opposition) and execute specific actions (e.g. eliminate the oppositions champion) appropriate to the imposed task demands (e.g. destroying the enemy's turret). Importantly, in esports like League of Legends, players require parallel processing, whereby multiple tasks have to be performed simultaneously. Furthermore, competition involves frequent decision-making moments that are continually adapted according to updated perceptual information in the performance environment. Traditionally, designing task representative methodologies that truly encapsulate the entire decision-making process is difficult (Williams & Ericsson, 2005). Specifically, it remains difficult to develop task representative designs that allow participants to (re)produce the behaviours observed in a real-world environment while maximising the control that can be exerted over an assessment (Hadlow et al., 2018).

Advancements in technology offers researchers the opportunity to develop assessments that are able to more readily represent the requirements of a task *in situ* (Williams & Ericsson, 2005). For example, in sport, despite involving more complex, dynamic, and open environments, researchers are also pursuing more task representative designs (Pinder et al., 2015). Researchers have opted to use video display technology (e.g., television screens, computer monitors, and video projector screens) coupled with simulated responses (e.g., pressing a button or key and moving a joystick or mouse) in the pursuit of developing externally valid tasks (Savelsbergh et al., 2002; Vaeyens et al., 2007). Although these methodologies afford researchers high levels of control, they still involve a significant degree of simulation as opposed to real perceptual cues and motor tasks, which will inadvertently alter the perception-action coupling of a real-world environment (Hadlow et al., 2018; Kelso & Kay, 2016). However, esports players identify and process visual information displayed on a digital screen, 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. As human-computer interaction mediates esports performance, the perception-action coupling experienced during performance can be accurately replicated in a controlled laboratory setting (Abernethy, Baker, & Côté, 2005; Pluss et al., 2019). Therefore, the current study aimed to assess the test-retest reliability and construct validity and of a commonly used online esports perceptual-motor skill assessment using an expertise paradigm. Given the assessment is proposed as an assessment and training tool for esports players, it was hypothesised that there will be minimal differences between the results of successive measures of the same measure carried out under the same conditions in terms of test-retest reliability. Regarding construct validity, it was hypothesised that esports players would demonstrate superior skill performance compared with the control group.

Methods

Participants

Data were collected from 40 participants (age: 24.15 ± 3.68 y, sex: male = 31, female = 9). Participants were *a priori* classified into two expertise groups: (1) esports players (age: 22.98 ± 3.64 y, sex: male = 18, female = 2), and (2) control (age: 25.31 ± 3.42 y, sex: male = 13, female = 7). All participants were from the Oceania region (Australasia, Melanesia, Micronesia, and Polynesia). The esports group consisted of multiplayer online battle arena players that participate in League of Legends (an average of 270.8 ± 169.23 games played since the start date of the current ranked season – 10th of January 2020 and the data collection dates – 3rd – 28th of May 2020). The average game length of League of Legends is approximately 30-45 minutes. The competitive rank distribution of the players included within this study is as follows: Silver = 4 (top 69.2 – 40.6 % of players, approximately 87.5 – 131.8 hours played in the current ranked season), Gold = 1 (top 34.3 – 13.6 % of players, approximately 93.5 – 140.3 hours played in the current ranked season), Platinum = 6 (top 10.8 – 3.5 % of players, approximately 175.7 – 263.5 hours played in the current rank season), Diamond = 7 (top 2.5 – 0.26 % of players, approximately 100.5 – 150.8 hours played in the current ranked season), Masters = 1 (top 0.085 – 0.051 % of players, approximately 181 – 271.5 hours played in the current ranked season), and Challenger = 1 (top 0.015 % of players, approximately 324.5 – 486.75 hours played in the current ranked season). 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 assess the test-retest reliability and construct validity of an esports perceptual-motor skill assessment. Participants completed a standardised walkthrough (task description and instructions on how the testing procedure is conducted) to ensure participants understood the task at hand. Following, participants completed a 10-minute familiarisation period under the same testing conditions as the assessment, which helps to minimise any learning effects and also accounts for individual differences in the responsiveness to a novel assessment. Subsequently, participants performed three separate trials of the assessment with a five-minute break between trials, whereby the aim was to achieve the highest score possible. A single trial of the assessment lasted 60 seconds. Participants completed the assessment with personal equipment (i.e. mouse and keyboard) and preferred settings (i.e. mouse sensitivity).

Esports perceptual-motor skill assessment

The esports perceptual-motor skill assessment was the Mobalytics Proving Ground Test (https://pg.mobalytics.gg/). Figure 6.1 provides a visual representation of the esports perceptual-motor skill assessment. The assessment is a game designed to test the mechanical ability, background processing, and map awareness of a League of Legends player. Mechanics – which refers to the ability to manipulate a mouse and keyboard to a perceptual stimulus – were assessed by a participant's ability to click quickly and accurately on targets that randomly appear around the screen. Clicking the bullseye rewards more points, whereas inaccurate clicking or ignoring targets (failing to click on them before the disappear from the screen) results in a loss of points. On the left side of the screen are four bars that randomly start depleting over several seconds. Participants were required to press the key (e.g. Q, W, E and R, which are the default keys for the champion abilities in League of Legends) that corresponded with each bar when the bar displayed a visual signal, which was when the bar turned from red to green in the final moments. Pressing the wrong key or letting the bar deplete completely resulted in the bar locking out for five seconds, which cost the opportunity to score more points. At the bottom right of the screen, there is a separate task designed to draw attention to a similar area of the screen as the map in League of Legends. For map awareness, the goal is to dodge (move right = F and move left = D, which are the default keys for the summoner spells in League of Legends) the obstacles that block the path. Contacting the obstacle will result in the participant being stuck until they move, which subsequently limits the opportunity to score more points. Overall, each of these tasks simulate the gameplay aspects of League of Legends. Table 6.1 details the variables for each of the performance characteristics (e.g. mechanics, background processing, and map awareness).

Figure 6.1. A visual representation of the esports perceptual-motor skill assessment.

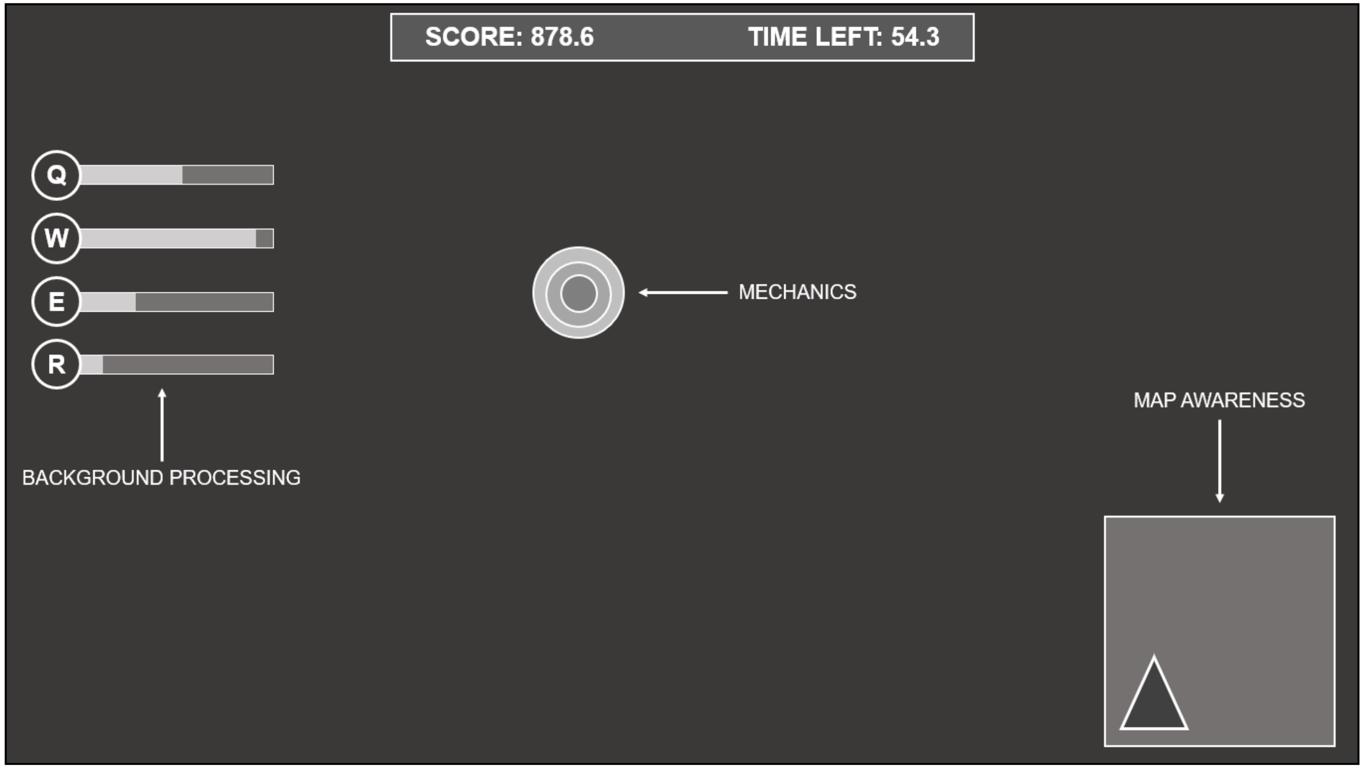


Table 6.1. The variables for each of the main performance characteristics measured in the esports perceptual-motor skill assessment.

Performance characteristics			
Total	**Mechanics**	**Background processing**	**Map awareness**
Total score (n)	Target hits (n)	Target hits (n)	Score (n)
Mechanics (n)	Accuracy (%)	Accuracy (%)	Time stuck (s)
Background processing (n)	Precision (%)	Precision (%)	Points lost (n)
Map awareness (n)	Targets ignored (n)	Targets ignored (n)	Average time per obstacle (s)
	Total points lost (n)		
	Centre hits (n)		
	Centre hits of all hits (n)		
	Points from centre hits (n)		
	Middle hits (n)		
	Middle hits of all hits (n)		
	Points from middle hits (n)		
	Border hits (n)		
	Border hits of all hits (n)		
	Points from border hits (n)		
	Average click delays (s)		
	Actions per minute (n)		
	Centre points lost (n)		
	Target hits (n)		

Statistical analysis

Normality was assessed via Shapiro-Wilk tests and histograms using the "mvn" package (Korkmaz, Goksuluk, & Zararsiz, 2014). To assess test-retest reliability, variables displaying normal distributions were analysed using intraclass correlation coefficient (ICC) estimates for single measures, two-way mixed effects models with 95% confidence intervals. The analysis was conducted using the "irr" package (Garmer, Lemon, Fellows, & Singh, 2014) and interpretations of the ICC were made using recommendations from Koo and Li (2016), i.e. < 0.50 = poor; 0.50 - 0.75 = moderate; 0.75 - 0.90 = good; > 0.90 = excellent. Variables which did not display normal distributions were analysed using Friedman tests, followed by post hoc comparisons using Wilcoxon signed rank tests and Bonferroni corrections for multiple comparisons. These analyses were conducted using the "rstatix" package (Kassambara, 2019). A criterion alpha level significance was set at $p < 0.05$ to identify significant differences between trials, and an effect size was calculated using Kendall's W with interpretations as 0.1 - 0.3 (small effect), 0.3 - 0.5 (moderate effect) and > = 0.5 (large effect). To assess the construct validity of the assessment, the trial in which each participant produced their best total score was used due to suspected lack of stability in scores across trials and non-normal distributions for most variables. Construct validity was assessed by comparing the esports group with the control group using Mann-Whitney U tests with a Bonferroni-corrected alpha level of $p < 0.0017$ ($p = 0.05 / 30$ tests) identifying significant differences between the two groups. All statistical analyses were conducted using R statistical software (R Development Core Team, New Zealand).

Results

Table 6.2 displays the median ± interquartile range for individual trials along with significant differences between groups for best trials (Bonferroni-corrected alpha level of $p < 0.0017$). Table 6.3 reports the assessment of normal distributions, intraclass correlation coefficients, 95% confidence intervals, and rating for all the data. Table 6.4 contains the results of the Friedman tests, which includes the p-value, effect size, rating, and the post hoc comparisons that compared each of the three trials for each group.

Table 6.2. Median and interquartile range for each trial and aggregated values for the trials were each player achieved their best scores per group.

	Trial 1		Trial 2		Trial 3		Aggregated best trial per player	
Independent variables	**Control**	**Esports**	**Control**	**Esports**	**Control**	**Esports**	**Control**	**Esports**
Total score (n)	943 (370.9)	1338.2 (111.1)	855.6 (300.4)	1404 (214.9)	1009 (303.8)	1371.3 (205.3)	1016.9 (251.7)	1424.2 (148.3)*
Mechanics (n)	47.5 (21.5)	74.5 (3.5)	48 (16.5)	76.5 (7.5)	49 (12.5)	77 (7.5)	49 (18.5)	79 (8)*
Background processing (n)	11.8 (13.4)	21 (12.8)	9.3 (13.8)	26 (15.8)	11.7 (12.3)	23.3 (13.8)	15.9 (14.8)	24.8 (11.5)
Map awareness (n)	48.9 (40.6)	75.5 (15.1)	41.4 (40)	83.6 (21.4)	59 (25.6)	84.7 (21.9)	61 (24.7)	82.8 (19.8)
Mechanics								
Target hits (n)	62.5 (43.8)	113 (6.5)	63 (35.2)	114 (5.2)	66 (39.2)	115 (3)	68 (39.2)	114 (5)*
Accuracy (%)	90 (10)	90 (2.5)	85 (10)	90 (10)	90 (10)	90 (10)	90 (10)	100 (10)*
Precision (%)	34.5 (26.5)	69 (6.2)	33.5 (23)	71.5 (8.5)	36.5 (19.2)	71 (10.2)	36.5 (23.2)	73.5 (8.2)*
Targets ignored (n)	48.5 (42.5)	1 (4.2)	49 (33.5)	2 (4.2)	46 (42)	1 (2.2)	47 (40.5)	1 (4.2)*
Total points lost (n)	416.5 (214.5)	180 (28.5)	423.5 (185.5)	171.5 (51.5)	416.5 (167.5)	164.5 (61)	409 (180.8)	151 (54)*
Centre hits (n)	30.5 (13.8)	47.5 (9)	32 (12.5)	51.5 (12.8)	29 (11.8)	51.5 (18.2)	39.5 (18.5)	50 (10.5)*
Centre hits of all hits (n)	40 (16.2)	42 (8)	42.5 (24.2)	45.5 (10.5)	39.5 (18.8)	45.5 (15.2)	39.5 (18.5)	50 (10.5)
Points from centre hits (n)	152.5 (68.8)	237.5 (46)	160 (62.5)	257.5 (63.8)	145 (58.8)	257.5 (78.8)	157.5 (72.5)	272 (65)*
Middle hits (n)	29 (22.2)	48 (6.8)	26 (19.5)	46.5 (7.8)	32.5 (26.8)	47 (12.2)	34 (23.5)	44 (9.5)
Middle hits of all hits (n)	43 (8.5)	42 (5.2)	41.5 (13)	41.5 (5.5)	44 (18.2)	41.5 (10)	43 (9.5)	39 (7.2)
Points from middle hits (n)	87 (66.8)	144 (20.2)	78 (58.5)	139.5 (23.2)	97.5 (80.2)	141 (36.8)	102 (70.5)	132 (28.5)
Border hits (n)	8.5 (10.8)	15.5 (7)	8 (13.2)	13 (8.2)	8.5 (9.2)	12 (7)	9.5 (9.5)	10 (7.5)
Border hits of all hits (n)	13.5 (10.2)	13 (5.8)	12.5 (12.8)	10.5 (8.2)	12.5 (9)	10 (6.8)	12.5 (9)	8.5 (6.5)
Points from border hits (n)	8.5 (10.8)	15.5 (7)	8 (13.2)	13 (8.2)	8.5 (9.2)	12 (7)	9.5 (9.5)	10 (7.5)
Average click delays (s)	1.6 (0.6)	0.8 (0.5)	1.6 (0.6)	0.9 (0.4)	1.5 (0.6)	0.9 (0.4)	1.4 (0.6)	0.8 (0.3)*
Actions per minute (n)	121 (40.2)	167.5 (18.2)	114.5 (49.5)	168 (12.2)	115.5 (46)	165 (13)	119.5 (46.8)	165 (17.5)*
Centre points lost (n)	316 (139.2)	329.5 (109.8)	329 (95.2)	173.5 (29.2)	165.5 (38)	157.5 (55.2)	324.5 (109)	147 (47)*
Background processing								
Score (n)	115.3 (89.5)	178 (94.6)	98.8 (125.8)	213.3 (105.2)	114.3 (99)	207.6 (107.5)	146.2 (109)	208.3 (102)*
Points lost (n)	384.7 (89.5)	322 (94.6)	401.2 (126)	322 (94.6)	385.7 (98.2)	292.4 (107.5)	353.9 (109)	291.6 (102)*
Total number of block bars (n)	17.5 (6.2)	11.5 (5.5)	18 (8.5)	9.5 (6)	16 (7.5)	10 (5.2)	16 (10)	9 (5.5)*
Time locked out (s)	64.3 (28.3)	40.1 (29.6)	69.4 (39.8)	34.2 (25.8)	61 (28.6)	40.4 (21.3)	62 (39)	30.5 (18.1)*
Map awareness								
Score (n)	244.3 (203.1)	377.6 (75.2)	207 (200.2)	418.1 (106.7)	295 (127.8)	423.2 (109.5)	305.2 (122.9)	414.4 (99)
Time stuck (s)	7.7 (7.1)	3.5 (2.1)	9.3 (6.8)	2.4 (3.1)	6 (4)	2.2 (3.1)	5.7 (5.3)	2.5 (2.8)
Points lost (n)	255.7 (203.1)	122.5 (75.2)	293 (200.2)	82 (106.7)	205 (127.9)	76.8 (109.5)	194.8 (123.2)	85.7 (99)
Average time per obstacle (s)	0.8 (0.6)	0.4 (0.2)	0.8 (0.5)	0.3 (0.3)	0.6 (0.4)	0.4 (0.2)	0.6 (0.4)	0.3 (0.2)*
Obstacles avoided (n)	0 (0)	0 (1)	0 (0)	0 (1.2)	0 (1)	0 (2.2)	0 (1)	0.5 (3)

*Note: n = number, % = percent, s = seconds, * = significant difference between groups (Bonferroni corrected alpha level = 0.05 / 30 = 0.00170).*

Test-retest reliability

In terms of the distribution of the data, seven out of 30 independent variables followed a normal distribution in the control group, whereas 17 out of 30 independent variables followed a normal distribution in the esports group. The average ICC for all independent variables in the control group was 0.72 (range: 0.15 – 0.94), and 0.53 (range: 0.14 – 0.91) in the esports group. The average 95% confidence intervals for the independent variables in the control group was 0.55 – 0.86 (range: 0.04 – 0.97), and 0.30 – 0.75 (range: 0.00 – 0.96) in the esports group. Overall, the reliability of the different variables obtained from the assessment ranged from poor – good reliability in both the control and the esports group. In terms of the Friedman test, seven of the independent variables reported a significance level of $p < 0.05$ in the control group, whereas nine independent variables reported a significance level of $p < 0.05$ in the esports group. The average effect size for the independent variables in the control group was 0.07, and 0.11 in the esports group. Overall, all effect sizes of the independent variables were rated as small for both groups (Kendall's W). When comparing results from trial 1 and trial 2, significant differences ($p < 0.05$) were observed in background processing score (n) and background processing points lost (n) in the esports group. When comparing results from trial 1 and trial 3, significant differences ($p < 0.05$) were observed in total score (n), map awareness (n), mechanics actions per minute (n), map awareness score (n), map awareness time stuck (n), and map awareness points lost (n) in the control group. Whereas in the esports group, significant differences ($p < 0.05$) were observed in total score (n), and mechanics precision (%). When comparing results from trial 2 with trial 3, a significant difference ($p < 0.05$) was observed in mechanics targets ignored (n) in the esports group only

Construct-validity

Across the 30 independent variables, there were 17 significant differences ($p < 0.0017$) observed when comparing the best scores of the esports group with the control group. In terms of the main performance characteristics outputs, total score (n) and background processing (n) were significantly ($p < 0.0017$) different between groups. Whereas there were no significant differences ($p > 0.0017$) with background processing (n) and map awareness (n) between groups. The majority of the variables (10 out of the 17 variables) associated with the mechanic aspect of the assessment were significantly ($p < 0.0017$) different between groups. All variables associated with the background processing aspect of the assessment were significantly ($p < 0.0017$) different between groups. However, only 1 out of the 5 variables associated with the map awareness aspect of the assessment were significantly ($p < 0.0017$) different between groups.

Table 6.3. The distribution, intraclass correlation coefficients, 95% confidence intervals, and rating for all the data.

	Normal distribution		ICC		95% CI		Rating	
Independent variables	**Control**	**Esports**	**Control**	**Esports**	**Control**	**Esports**	**Control**	**Esports**
Total score (n)	Yes	Yes	0.74	0.50	0.52 - 0.88	0.23 - 0.74	moderate - good	poor - moderate
Mechanics (n)	No	No	0.87	0.65	0.76 - 0.94	0.42 - 0.83	good - excellent	poor - good
Background processing (n)	No	Yes	0.29	0.58	0.04 - 0.58	0.33 - 0.78	poor - moderate	poor - good
Map awareness (n)	No	No	0.65	0.45	0.41 - 0.83	0.18 - 0.70	poor - good	poor - moderate
Mechanics								
Target hits (n)	No	No	0.94	0.72	0.87 - 0.97	0.52 - 0.87	good - excellent	moderate - good
Accuracy (%)	No	No	0.61	0.73	0.37 - 0.80	0.53 - 0.87	poor - good	moderate - good
Precision (%)	No	Yes	0.91	0.58	0.82 - 0.96	0.33 - 0.79	good - excellent	poor - good
Targets ignored (n)	No	No	0.94	0.64	0.88 - 0.97	0.39 - 0.82	good - excellent	poor - good
Total points lost (n)	No	Yes	0.92	0.57	0.83 - 0.96	0.32 - 0.78	good - excellent	poor - good
Centre hits (n)	Yes	Yes	0.65	0.53	0.42 - 0.83	0.27 - 0.76	poor - good	poor - good
Centre hits of all hits (n)	No	Yes	0.83	0.51	0.69 - 0.92	0.25 - 0.74	moderate - excellent	poor - moderate
Points from centre hits (n)	Yes	Yes	0.65	0.53	0.42 - 0.83	0.27 - 0.75	poor - good	poor - good
Middle hits (n)	No	Yes	0.84	0.32	0.69 - 0.93	0.04 - 0.61	moderate - excellent	poor - moderate
Middle hits of all hits (n)	Yes	Yes	0.57	0.27	0.32 - 0.78	0.00 - 0.57	poor - good	poor - moderate
Points from middle hits (n)	No	Yes	0.84	0.32	0.69 - 0.93	0.04 - 0.61	moderate - excellent	poor - moderate
Border hits (n)	No	Yes	0.87	0.56	0.74 - 0.94	0.30 - 0.77	moderate - excellent	poor - good
Border hits of all hits (n)	Yes	No	0.73	0.56	0.53 - 0.87	0.31 - 0.77	moderate - good	poor - good
Points from border hits (n)	No	Yes	0.87	0.56	0.74 - 0.94	0.30 - 0.77	moderate - excellent	poor - good
Average click delays (s)	No	No	0.93	0.91	0.86 - 0.97	0.83 - 0.96	good - excellent	good - excellent
Actions per minute (n)	Yes	No	0.86	0.89	0.74 - 0.94	0.79 - 0.95	moderate - excellent	good - excellent
Centre points lost (n)	Yes	Yes	0.89	0.56	0.79 - 0.95	0.31 - 0.77	good - excellent	poor - good
Background processing								
Score (n)	No	Yes	0.57	0.53	0.31 - 0.78	0.27 - 0.76	poor - good	poor - good
Points lost (n)	No	Yes	0.57	0.53	0.31 - 0.78	0.27 - 0.76	poor - good	poor - good
Total number of block bars (n)	Yes	Yes	0.70	0.54	0.47 - 0.85	0.28 - 0.76	poor - good	poor - good
Time locked out (s)	Yes	Yes	0.79	0.61	0.62 - 0.90	0.36 - 0.80	moderate - excellent	poor - good
Map awareness								
Score (n)	No	No	0.65	0.45	0.41 - 0.83	0.18 - 0.70	poor - good	poor - moderate
Time stuck (s)	No	No	0.15	0.40	0.09 – 0.46	0.13 - 0.66	poor - poor	poor - moderate
Points lost (n)	No	No	0.65	0.45	0.41 - 0.83	0.18 - 0.70	poor - good	poor - moderate
Average time per obstacle (s)	No	No	0.46	0.14	0.19 - 0.71	0.09 - 0.44	poor - moderate	poor - poor
Obstacles avoided (n)	No	No	0.65	0.44	0.42 - 0.83	0.17 - 0.69	poor - good	poor - moderate

Note: ICC = intraclass correlation coefficient estimates, CI = confidence intervals, n = number, % = percent, s = seconds.

Table 6.4. The results of the Friedman test and the post hoc comparisons that compared each of the three trials for each group.

	p-value		**ES**		**Rating**		**T1 v T2**		**T1 v T3**		**T2 v T3**	
Independent variables	**Control**	**Esports**	**Control**	**Esports**	**Control**	**Esports**	**Control**	**Esports**	**Control**	**Esports**	**Control**	**Esports**
Total score (n)	0.02*	0.01*	0.20	0.23	small	small	1.00	0.25	0.01*	0.00*	0.06	0.27
Mechanics (n)	0.31	0.04*	0.06	0.16	small	small	1.00	1.00	0.67	0.10	0.53	0.45
Background processing (n)	0.29	0.09	0.06	0.12	small	small	1.00	0.09	0.97	0.32	0.23	1.00
Map awareness (n)	0.04*	0.08	0.16	0.13	small	small	1.00	0.53	0.02*	0.06	0.11	1.00
Mechanics												
Target hits (n)	0.37	0.40	0.05	0.05	small	small	1.00	1.00	0.13	0.91	0.33	0.65
Accuracy (%)	0.34	0.09	0.05	0.12	small	small	0.46	0.29	1.00	0.83	1.00	1.00
Precision (%)	0.38	0.01*	0.05	0.23	small	small	1.00	1.00	0.22	0.05*	0.27	0.13
Targets ignored (n)	0.45	0.03*	0.04	0.17	small	small	1.00	0.56	0.22	0.26	0.88	0.02*
Total points lost (n)	0.39	0.02*	0.05	0.19	small	small	1.00	1.00	0.16	0.09	0.50	0.08
Centre hits (n)	0.89	0.38	0.01	0.05	small	small	1.00	1.00	1.00	0.34	1.00	0.95
Centre hits of all hits (n)	0.91	0.92	0.01	0.00	small	small	1.00	1.00	1.00	0.65	1.00	1.00
Points from centre hits (n)	0.89	0.19	0.01	0.08	small	small	1.00	1.00	1.00	0.23	1.00	0.65
Middle hits (n)	0.14	0.82	0.10	0.01	small	small	1.00	1.00	0.18	1.00	0.06	1.00
Middle hits of all hits (n)	0.84	0.85	0.01	0.01	small	small	1.00	1.00	1.00	1.00	0.64	1.00
Points from middle hits (n)	0.14	0.82	0.10	0.01	small	small	1.00	1.00	0.18	1.00	0.06	1.00
Border hits (n)	0.83	0.43	0.01	0.04	small	small	1.00	1.00	1.00	0.38	1.00	1.00
Border hits of all hits (n)	0.29	0.13	0.06	0.10	small	small	1.00	1.00	0.32	0.24	0.45	0.37
Points from border hits (n)	0.83	0.43	0.01	0.04	small	small	1.00	1.00	1.00	0.38	1.00	1.00
Average click delays (s)	0.69	0.22	0.02	0.08	small	small	1.00	1.00	1.00	1.00	1.00	1.00
Actions per minute (n)	0.05*	0.53	0.15	0.03	small	small	1.00	0.13	0.04*	1.00	0.23	1.00
Centre points lost (n)	0.39	0.02*	0.05	0.19	small	small	1.00	1.00	0.38	0.13	0.89	0.15
Background processing												
Score (n)	0.52	0.05*	0.03	0.15	small	small	1.00	0.03*	1.00	0.23	0.83	1.00
Points lost (n)	0.52	0.05*	0.03	0.15	small	small	1.00	0.03*	1.00	0.23	0.83	1.00
Total number of block bars (n)	0.61	0.04*	0.03	0.16	small	small	1.00	0.12	1.00	0.19	1.00	1.00
Time locked out (s)	0.64	0.26	0.02	0.07	small	small	0.65	0.50	1.00	0.46	1.00	1.00
Map awareness												
Score (n)	0.04*	0.08	0.16	0.13	small	small	1.00	0.52	0.02*	0.07	0.11	1.00
Time stuck (s)	0.02*	0.06	0.19	0.14	small	small	1.00	0.65	0.04*	0.07	0.08	1.00
Points lost (n)	0.04*	0.08	0.16	0.13	small	small	1.00	0.53	0.02*	0.07	0.11	1.00
Average time per obstacle (s)	0.03*	0.19	0.18	0.08	small	small	0.66	0.69	0.15	0.12	0.33	1.00
Obstacles avoided (n)	0.09	0.15	0.12	0.10	small	small	0.80	0.13	0.17	0.17	1.00	1.00

*Note: ES = effect size, T1 = trial 1, T2 = trial 2, T3 = trial 3, n = number, % = percent, s = seconds, * = a significant difference between trials ($p < 0.05$).*

Discussion

The current study investigated the test-retest reliability and construct validity of an esports perceptual-motor skill assessment using an expertise paradigm. The assessment used in the present study was a game designed to test the mechanical ability, background processing, and map awareness of a League of Legends player. Overall, most of the independent variables followed a non-normal distribution, particularly in the control group, resulting in most comparisons relying on non-parametric analyses with reduced power. Given the poor test-retest reliability present across the three separate trials, using the best scores for each of the independent variables was deemed necessary to conduct group-wise comparisons. In terms of the main performance characteristics, the esports group demonstrated superior skill performance in total score and mechanics compared with the control group, however background processing and map awareness did not discriminate between groups. When analysing the variables related to each aspect of the main performance characteristics (e.g. mechanics, background processing, and map awareness), the majority of variables associated with mechanics and background processing significantly differed between groups. Whereas some of variables associated with mechanics map awareness did not discriminate between groups. As a result, the esports perceptual-motor skill assessment used in the current study can to some extent discriminate between an esports player and a control group. However, the assessment has limited applicability when aiming to quantify some of the main performance characteristics of an esports player.

The esports perceptual-motor skill assessment lacked test-retest reliability and there was a lack of stability of different performance measures within the task across multiple trials. It is likely that one of the main issues with the reliability of the data is the lack of a clear task goal within the assessment. The primary aim of the assessment is to achieve the highest score possible, which is determined by performance across the three separate tasks. Whereas there are clear and defined objectives in competition, such as eliminating the oppositions champion followed by destroying the enemy's turret and inhibitors. As such, the nature of the objective associated with the assessment used in this study was rather arbitrary, whereby performance across the tasks may be influenced by individual discretion. For example, in one trial a participant may have focused on scoring as many possible points possible in the background processing task. Yet, for the next trial the same participant may have focused on scoring as many points possible in the map awareness task. However, as visual selective attention was not measured within the current study, the authors cannot provide any further support to whether this was a contributing factor underlying the reliability of the data. Therefore, future research should utilise eye-tracking technology to measure visual selective attention to minimise the influence this may have on the data when assessing the reliability of an esports perceptual-motor skill assessment.

Although the current study incorporated more domain-specific measure (i.e. a commonly used task developed to assess and train League of Legends players) of esports performance, many of the variables obtained from this task were not associated with esports expertise. This finding is likely the result of the reduced specificity in the perception-action coupling of aspects of the assessment (Hadlow et al., 2018). For example, with the background processing task, there were several bars which would randomly start depleting on the left side of the screen. Participants were required to press the key (e.g. Q, W, E and R) that corresponded with each bar when the bar displayed a visual signal, which was when the bar turned from red to green. However, in competition, the players ability bar is located at the bottom of the screen. Furthermore, players press the keys (e.g. Q, W, E and R) based off a cool-down timer, which is presented numerically (seconds) instead of a change in colour. Another example is the map awareness task, whereby the goal is to dodge (move right = F and move left = D) the obstacles that block the path. Although in competition, the mini map is located in the bottom right-hand corner of the screen. Players typically divert attention towards the mini map to receive information, such as the opponent's position on the map, where the team has vision, and what objectives are coming up next. However, players are not required to execute specific actions appropriate to the imposed task demands similar within the assessment. Similarly, other studies that used assessments with non-specific actions presented limited evidence to support their employed methodological design's validity (Bennett, Novak, Pluss, Coutts, & Fransen, 2019; Keller, Raynor, Iredale, & Bruce, 2018; O'Connor, Larkin, & Mark Williams, 2016). Therefore, it is important when designing assessments aimed at quantifying performance characteristics in esports to incorporate specific actions that accurately replicate the task demands of competition.

Inherently, there are limitations present within the current study. First, given the poor test-retest reliability, 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 minimise the influence this may have, participants were encouraged to only proceed if they were comfortable to perform the task. Second, given the limited applicability when aiming to quantify some of the performance characteristics of an esports player, the data obtained from this assessment may only provide an indication of an esports players perceptual-cognitive expertise.

Conclusion

The current study aimed to assess the test-retest reliability and construct validity and of an esports perceptual-motor skill assessment using an expertise paradigm. Overall, the esports perceptual-motor skill assessment used in the current study can discriminate to some extent between an esports player and a control group. However, given the poor test-retest reliability and poor construct validity, the Mobalytics Proving Ground Test is not a suitable tool for quantifying the performance characteristics of an esports player in League of Legends. Therefore, it is important that assessments aimed at quantifying performance characteristics in esports to incorporate specific actions that accurately replicate the task demands of competition.

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Disclosure statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that would be construed as a potential conflict of interest.

Chapter 7:

Study 5

The relationship between the quantity of practice and in-game performance during practice with tournament performance in esports: An eight-week prospective study

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Abstract

This study aimed to examine the influence of the quantity of practice and the in-game performance during practice of professional esports players over an eight-week period immediately prior to a major esports tournament. Data was collected from 43 male professional esports players (age: 23.52 ± 2.50 y). A range of measures were collected on a weekly basis to describe the quantity of practice and represent in-game performance during practice. The relationship between practice and tournament performance were examined using individual linear mixed-effects models for each week prior to competition. In a final linear mixed-effects model which incorporated the relevant variables identified within the weekly models identified a significant average kill/death ratio + average score main effect on tournament performance ($p < 0.001$, $R^2 = 0.30$). With every standard deviation increase in average kill/death ratio, there was a 7.94% increase in tournament score (95% CI: 3.86 – 12.18%, $t = 3.89$, $p = < 0.001$). With every standard deviation increase in average score, there was a 6.40% increase in tournament score (95% CI: 2.40 – 10.56%, $t = 3.17$, $p = 0.003$). Overall, the quantity of practice and in-game performance during practice explain a small proportion of the variance in tournament performance. More specifically, the variables that are most associated with better tournament performance are kill/death ratio and the score obtained in practice during the lead up to competition. Interestingly, the quantity of accumulated and weekly practice had limited association with better tournament performance. Whether the association between practice and performance differs depending on players' expertise levels requires future research.

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). Participation in esports has risen exponentially over several decades, now with a population of over 100 million players worldwide (Novak et al., 2019). Despite high recreational participation rates, only a small number of players (a few hundred to several thousand depending on the video game) compete as professionals (Novak, Bennett, Pluss, & Fransen, 2020). While 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 et al., 2018). Although the motivations (e.g. competition, passion, and social reasons) for pursuing a career in esports are documented (García-Lanzo & Chamarro, 2018; Kahn et al., 2015; Yee, 2006), the attainment of expertise in esports has received considerably less attention (Pluss et al., 2020) despite being investigated extensively in other fields such as music, sport, medicine and academia (Ericsson, 2006; Ericsson et al., 1993; Starkes & Ericsson, 2003). At the forefront of expertise research are studies examining the practice activities (i.e. the frequency and type of practice) of an individual. Furthermore, researchers further explore how the amount of practice an individual engages in relates to attaining expertise (Baker et al., 2003; Charness et al., 2005; Côté et al., 2007; Ericsson, 2006). Overall, extensive engagement in domain-specific activities (e.g. competition, organised training, and individual practice) is necessary to attain expert performance (Ericsson et al., 1993; Ward et al., 2007). In many domains, the attainment of expertise can be influenced by the time engaged in practice (Baker, 2003; Baker et al., 2009; Mattson & Richards, 2010). As a result, researchers have focused on identifying which type of practice is most beneficial for developing expertise, as this information can assist with improving the effects of practice (Ericsson et al., 1993). Some researchers argue that practice has to be deliberate and purposeful to attain expertise (Charness et al., 2005; Ericsson et al., 1993). While, other authors argue that engaging in a wide range of activities, especially at an early age, is beneficial for the development of expertise as an enduring characteristic (i.e. sampling leads to longer careers) (Bridge & Toms, 2013; Goodway & Robinson, 2015). Despite this, it is generally accepted that the amount of practice an individual engages in is related to the attainment of expertise across many domains (Ericsson, 2020; Macnamara & Maitra, 2019). While research in esports is gaining traction, no research has investigated the influence of practice on performance in esports.

Many studies typically observe practice over extended periods of times (e.g. months to years), practice can also provide acute (e.g. days to weeks) performance outcomes (de Bruin, Smits, Rikers, & Schmidt, 2008; Deakin & Cobley, 2003). Understanding the acute effects practice has on performance is beneficial for players and coaches to support training of specific skills (Gaspar et al., 2019). Furthermore, there is an inherent belief that future performance is influenced by training in the weeks immediately preceding competition, in other words is you play as you train (Castillo-Rodríguez, Cano-Cáceres, Figueiredo, & Fernández-García, 2020; Ireland et al., 2019; Jones, Armour, & Potrac, 2003). Therefore, it is crucial to understand the relationship between practice and performance at an acute level, such as the preceding weeks of competition. Esports is novel in that practice settings (i.e. a mix of competitive game play under the same task constraints observed in competition and isolated practice activities) closely resemble competition contexts. This representativeness of practice environments is relatively uncommon in many other domains (Williams & Ericsson, 2005). For example, professional esports players undertake much of their practice by competing against other professional esports players in the same game under the same rules of competition, without requiring physical proximity due to the virtual nature of competition. An equivalent scenario in an association football context would be to have 22 of the world's best players from different teams and nations practice by competing in 90 minutes of 11 v 11 game-play on a full-sized pitch under the same rules of competition. As such, examining both the quantity of practice and the in-game performance measures during practice can help improve our understanding about the relationship between practice and performance. Therefore, the present study followed a prospective design to examine the quantity of practice and in-game performance measures during practice of professional players over an eight-week period immediately prior to a major esports tournament. Following previous work, it was hypothesised that the quantity of practice and in-game performance during practice in the weeks preceding a major competitive event will explain a small proportion of the variance in tournament performance (Macnamara, Moreau, & Hambrick, 2016; Young, 1998).

Methods

Participants

Data were collected from 43 male professional esports players (age: 23.52 ± 2.50 y) from 14 separate teams competing in the major esports tournament (PGL Major Krakow 2017). The professional esports players compete on a full-time basis and represent a professional esports team at the highest level of competition in a first-person shooter video game (Counter-Strike: Global Offensive). The professional esports players within this competition were from North America (n = 14) or Europe (n = 29). The Institutional Ethics Research Committee approved this study.

Experimental procedure

The study used an eight-week longitudinal design to examine how the quantity of practice and in-game performance measures during practice were related to performance in a major esports tournament (PGL Major Krakow 2017). In terms of the quantity of practice, the two main variables of interest were the *time spent in-game* and the *time spent in competition*. The time spent in-game is a combination of practice that is typically focused on developing individual skills and practice in a competitive team-based environment (*time spent in competition)*. The most common type of individual practice is practicing in deathmatch, which is a mode featuring instant respawns (allows players to respawn instantly after death, which is not evident in competition) with the ability to purchase any primary and secondary weapons with no regards to the money economy. Each match lasts 10 minutes and the player with the highest points wins the round. Whereas the time spent in competition involves practice solely in a competitive team-based environment. This type of practice involves two teams consisting of five players competing head-to-head in a 30-round match. The first team to score 16 points wins the game. After 15 rounds (half time), each team switches sides (T-side and CT-side). The T-side must plan C4 at a bombsite and the CT-Side must defend the bombsite. Each round is one minute and 45 seconds long, however, if the T-side team manages to plant the bomb then the round timer resets to 40 seconds. On average, a single competitive match will last approximately 40 minutes, though a competitive match can extend to over an hour if the match is close. If both teams reach 15 rounds each, the game will end in a tie. This study used publicly available data from each player's official Steam® profile and a third-party webpage (https://csgo-stats.com). As data was only collected from each player's main profile, any additional practice on alternative accounts (i.e. smurf accounts – an alternative account used by a known or experienced user in order to deceptively self-present as less experienced) was not accounted for within the present study and would be worthwhile to account for in future research. Data were collected at a standardised time on a weekly basis using a custom data scraping method developed in Python, which collated and stored all data into a Microsoft Excel spreadsheet. A labelling rule considered and discarded a data observation as an outlier when they were outside of the value associated with the values derived from multiplying each participants interquartile range (IQR) by 1.5, upon which values beyond the 25^{th} and 75^{th} percentiles $\pm 1.5 \times$ IQR (Hoaglin & Iglewicz, 1987; Hoaglin et al., 1986). After discarding outliers, the current study used a total of 284 observations from 43 participants (~6.6 observations per participant). Table 7.1 provides a description of the independent variables that were measured in the current study. These measures are commonly used for statistical analysis purposes to develop online rankings and determining match outcomes. The dependent variable was a player's standardized and normalised tournament score, which was calculated using the coefficient scores from a confirmatory factor analysis of the performance rating combined in a linear equation (Henderson et al., 2019). The following tournament performance metrics were introduced after being standardized and normalised into a quotient score with a mean of 100 and standard deviation of 15 (quotient score = 100 + (z-score*15): the kill/death difference quotient, kill/death ratio quotient, and solo rating (a proprietary calculation that assesses player performance) quotient. When controlling for low commonalities (< 0.4), the final tournament sum score was calculated as 0.977*kill/death difference quotient + 0.993*kill/death ratio quotient + 0.974*solo rating quotient. The Kaiser-Meyer-Olkin and Barlett's test demonstrated a considerable amount of variance that could be explained by the underlying factors (Kaiser-Meyer-Olkin measure of sampling accuracy: 0.70) and player performance could be presented as a single factor (Bartlett's test of Sphericity: $p < 0.001$).

Table 7.1. A description of the quantity of practice and in-game performance measures

Independent variable	Description
Quantity of practice	
Accumulated time spent in-game (hours)	Total amount of practice that typically involves practice focused on developing individual skills
Accumulated time spent in competition (hours)	Weekly amount of practice that typically involves practice in a competitive team-based environment
Weekly time spent in-game (hours)	Total amount of practice that typically involves practice focused on developing individual skills
Weekly time spent in competition (hours)	Weekly amount of practice that typically involves practice in a competitive team-based environment
Weekly matches played (n)	Weekly number of matches played
In-game performance measures	
Accumulated win percentage (%)	Total number of matches won/number of matches played
Weekly win percentage (%)	Weekly number of matches won/number of matches played
Weekly kills (n)	Number of enemies eliminated
Weekly deaths (n)	Being eliminated by an enemy
Weekly kill/death ratio (n)	Number of kills/number of deaths
Weekly score (n)	A proprietary calculation built in-game that indicates how well you are doing compared to the other players in the same game
Weekly matches won (n)	The result of a match, whether it resulted in a win or a loss
Weekly most valuable player stars (n)	Given to one player that has contributed the most towards winning a round – generally obtained more kills, conceded less deaths, and planted/diffused bombs

Statistical analysis

Prior to analysis, dependent variables' distribution was visually inspected using the boxplots and histograms. Additionally, homogeneity of variance was assessed at each level of analysis (e.g. dependent variable by player and dependent variable by week). Furthermore, collinearity of the independent variables was explored using correlation plots and correlation coefficients. A correlation coefficient cut-off of 0.80 was used to determine collinearity between independent variances (Onwuegbuzie & Daniel, 1999). In the case of multicollinearity, the independent variable with the strongest relationship with the dependent variable was retained. Seven separate linear mixed effects models (1 | Team) were applied to the data (one for each week of practice), each of which was developed using a step-up approach. This exploratory approach was used because no prior information was available about the relationship between practice and tournament performance in esports. In each step, a random intercepts null model was firstly specified. Then, subsequent models were compared with the null model or the previous step in the step-up approach where models with a significantly better model fit were retained. Whereas poorer fitting models were discarded according to the -2-log likelihood ratio test and associated p-value, Akaike Information Criterion explained variance and conditional explained variance. Random slope models were considered but not introduced given the likelihood of overfitting in this sample. In the next step of the analyses, the variables that were associated with tournament performance in the weekly models were introduced into a final model that explored the effect of the accumulated eight-weeks of practice on tournament performance. For example, if kill/death ratio is associated with tournament performance in one of the weekly models, its central tendency over the eight weeks was introduced into the final model as a quotient score (scaled z-score). This transformation enabled interpretation of weekly variation in the relationship between the independent and dependent variables (i.e. whether the relationship between practice and subsequent performance was time-dependent) and which variables appeared to be associated with performance over a longer and cumulative time spans. Scaled z-scores (coefficients), standard errors, t-values and 95% confidence intervals related to each significant independent variable were derived for further interpretation. Residual distribution plots associated Shapiro-Wilks tests, and Levene's tests were used to investigate how well the obtained models fit the data and whether homogeneity of residual variance was apparent. A criterion alpha level significance was set at $p < 0.05$. All statistical analyses were conducted using R statistical software (R Development Core Team, New Zealand).

Results

Figure 7.1 displays the average amount of time spent in-game and the average amount of time spent in competition each week out of competition (presented as mean ± SD). Table 7.2 displays the Akaike Information Criterion (AIC), explained variance (marginal R^2), conditional explained variance (conditional R^2), degrees of freedom (df) and the retained players (team) of the best fitting weekly models explaining tournament performance, as well as the best-fitting model with cumulative or average values over the eight-week period. At seven weeks out from competition, the linear mixed effects model identified a significant kill/death ratio + most valuable player stars main effect on tournament performance ($p = < 0.001$, AIC: -48.0, marginal $R^2 = 0.22$, conditional $R^2 = 0.67$, df: 5). At six weeks out from competition, the linear mixed effects model identified a significant kill/death ratio main effect on tournament performance ($p = < 0.001$, AIC: -34.4, marginal $R^2 = 0.12$, conditional $R^2 = 0.35$, df: 4). At five weeks out from competition, the linear mixed effects model identified a significant time spent in-game main effect on tournament performance ($p = < 0.001$, AIC: -37.4, marginal $R^2 = 0.17$, conditional $R^2 = 0.31$, df: 4). At four weeks out from competition, the linear mixed effects model identified a significant kill/death ratio main effect on tournament performance ($p = < 0.001$, AIC: -43.0, marginal $R^2 = 0.18$, conditional $R^2 = 0.47$, df: 4). At three weeks out from competition, the linear mixed effects model identified no significant main effects on tournament performance ($p > 0.05$). At two weeks out from competition, the linear mixed effects model identified a significant kill/death ratio main effect on tournament performance ($p = < 0.001$, AIC: -36.0, marginal $R^2 = 0.12$, conditional $R^2 = 0.25$, df: 4). At one week out from competition, the linear mixed effects model identified a significant kill/death ratio main effect on tournament performance ($p = < 0.001$, AIC: -37.1, marginal $R^2 = 0.09$, conditional $R^2 = 0.15$, df: 4). In the average model, the linear mixed effects model identified a significant average kill/death ratio + average score main effect on tournament performance ($p = < 0.001$, AIC: -120.4, marginal $R^2 = 0.30$, conditional $R^2 = 0.60$, df: 5). Table 7.3 displays the scaled z-scores (coefficients), 95% confidence intervals, p-value, t-value, obtained from best fitting models explained tournament performance each week out of competition, as well as from best fitting model with cumulative values over the eight-week period. In the average model, for every standard deviation increase in average kill/death ratio, there is a 7.9% increase in tournament score (95% confidence interval: 3.9 – 12.2, $t = 3.89$, $p = < 0.001$). Furthermore, with every standard deviation increase in average score, there is a 6.4% increase in tournament score (95% confidence interval: 2.4 – 10.6, $t = 3.17$, $p = 0.003$).

Table 7.2. The effects of accumulated values and weekly values on tournament performance.

Models	Best fitting weekly models explaining tournament score				
	AIC	**Marginal R^2**	**Conditional R^2**	**df**	**Players (team)**
Null: Score ~ 1 + (1 | Team)					
7 weeks out: Score ~ KD + MVP + (1 | Team)	-48.0	0.22	0.67	5	41 (14)
6 weeks out: Score ~ KD + (1 | Team)	-34.4	0.12	0.35	4	40 (14)
5 weeks out: Score ~ TSI + (1 | Team)	-37.4	0.17	0.31	4	40 (14)
4 weeks out: Score ~ KD + (1 | Team)	-43.0	0.18	0.47	4	39 (14)
3 weeks out: Null	N/A	N/A	N/A	N/A	N/A
2 weeks out: Score ~ KD + (1 | Team)	-36.0	0.12	0.25	4	41 (14)
1 week out: Score ~ KD + (1 | Team)	-37.1	0.09	0.15	4	40 (14)
Average: Score ~ Av KD + Av Score + (1 | Team)	-120.4	0.30	0.60	5	43 (14)

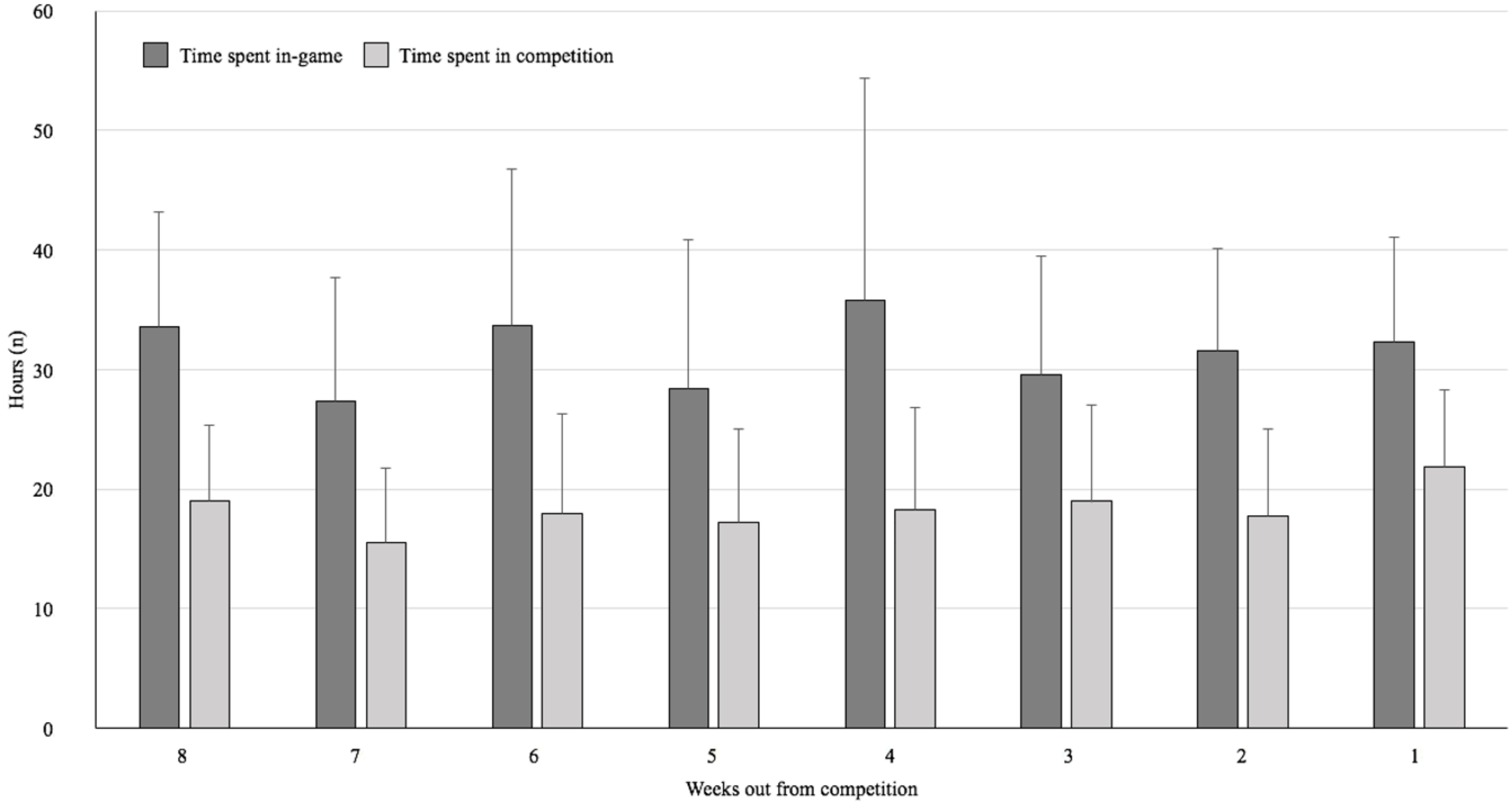
Note: AIC = Akaike Information Criterion, df = degrees of freedom, KD = kill/death ratio, MVP = most valuable player stars, TSI = time spent in-game, N/A = not applicable, Av = average. The term of players (team) refers to the number of players and (teams) observations after discarding outliers based on the labelling rule.

Table 7.3. The independent variables in the weekly models that were associated with better tournament performance.

	Coefficient	95% CI	t-value	p-value
		Intercept		
7 weeks out:	287.2	269.5 - 306.1		<0.001
6 weeks out:	290.4	276.5 - 304.9		<0.001
5 weeks out:	292.9	278.7 - 307.9		<0.001
4 weeks out:	290.2	274.8 - 306.4		<0.001
3 weeks out				
2 weeks out	290.3	275.6 - 305.8		<0.001
1 week out:	288.9	276.1 - 302.4		<0.001
Average:	291.24	275.57 - 307.80		<0.001
		Kill/death ratio (n)		
7 weeks out:	3.28	0.02 - 6.87	1.847	0.073
6 weeks out:	5.51	0.87 - 10.37	2.337	0.496
5 weeks out:				
4 weeks out:	6.53	2.39 - 10.84	3.132	0.003
3 weeks out				
2 weeks out	5.49	0.75 - 10.45	2.277	0.029
1 week out:	4.56	0.07 - 9.24	1.994	0.054
Average:	7.94	3.86 - 12.18	3.885	<0.001
		Most valuable player stars (n)		
7 weeks out:	5.36	1.78 - 9.06	2.964	0.006
6 weeks out:				
5 weeks out:				
4 weeks out:				
3 weeks out				
2 weeks out				
1 week out:				
Average:				
		Time spent in-game (n)		
7 weeks out:				
6 weeks out:				
5 weeks out:	-6.14	-10.42 - -1.44	-2.553	0.019
4 weeks out:				
3 weeks out				
2 weeks out				
1 week out:				
Average:				
		Score (n)		
7 weeks out:				
6 weeks out:				
5 weeks out:				
4 weeks out:				
3 weeks out				
2 weeks out				
1 week out:				
Average:	6.40	2.40 - 10.56	3.172	0.003

Note: CI = confidence interval. A blank row indicates that there is no significant association (p > 0.05) with tournament score.

Figure 7.1. The average amount of time spent in-game and the average amount of time spent in competition each week out of competition (presented as mean ± SD).



Discussion

The current study examined the quantity of practice and in-game performance during practice of professional esports players over an eight-week period in the lead up to a major esports tournament. Overall, the quantity of practice and in-game performance during practice explains a small proportion of variance in tournament performance. More specifically, the variables that are most associated with better tournament performance are kill/death ratio (amount of kills/number of deaths) and score (indicates how well you are doing compared to the other players in the same game) during the lead up to competition. When analysing the practice at a weekly basis, most of the variables associated with better tournament performance were measures of in-game performance during practice, rather than the quantity of practice. Evidentially, accumulated (total time spent in-game and total time spent in competition) and weekly (weekly time spent in-game and weekly time spent in competition) durations of practice had limited association with better tournament performance in professional esports players. Similarly, Macnamara et al. (2016) demonstrated that the accumulated quantity of practice accounted for 1% of the variance in performance among elite athletes in team and individual sports. Furthermore, Young (1998) reported that the total sum of all accumulated practice had no significant correlation ($r = 0.12$) with performance for middle distance runners. As such, this finding does not provide support that individual differences, even among professional esports players, are closely related to the accumulated quantity of practice (Ericsson, 2006; Ericsson et al., 1993; Ward et al., 2007). However, it is likely that practice which is deliberate and purposeful is necessary to reach a high level of expertise in esports. Despite this, it is apparent that there is more to differentiate between performance than the quantity of practice at the professional level. As such, tracking the quantity of practice over a longitudinal period with different expertise levels (i.e. semi-professional, amateur and recreational) remains an area for future research.

Esports practice is primarily conducted in an environment whereby the players actively respond to a task with an explicit goal, receive immediate formative feedback and repeatedly perform the same or similar tasks (Ericsson, 2020; Macnamara & Maitra, 2019). The time spent in-game typically involves practice focused on developing individual skills, whereas the time spent in competition involves practice in a competitive team-based environment. It is suggested that engaging in both types of practice is beneficial for the development of expertise. It is likely that involvement in these type of practice present esports players with different action sequences and situational contexts (Côté et al., 2007; Davids, Button, & Bennett, 2008). However, during the lead up to competition, the amount an individual engages in practice (average of 32 hours per week) is unlikely to lead to better tournament performance. Perhaps better tournament performance reflects having a specific focus during practice, whereby the goal is to maximise the number of enemies they eliminate and minimise the amount of times they are eliminated by an enemy. Practicing in this manner is largely implicit driven and players must self-discover their own solutions to the task, which may explain the acute effects that practice has on tournament performance (Côté et al., 2003). However, future research is needed to support this hypothesis as the specific goals and motives of an esports players during practice were not measured within the present study.

The kill/death ratio of a player was the most significant variable associated with tournament performance over the eight-week period. Furthermore, kill/death ratio is often seen as one of the most effective ways to evaluate an individual's in-game performance in many different esports genres, in particular, first-person shooters (i.e. Counter-Strike:

Global Offensive, Call of Duty, and Overwatch). Players outperforming their opponents is achieved by a kill/death ratio greater than 1.0, whereas a player underperforming will have a kill/death ratio less than 1.0. Despite being an indicator of individual performance, considerations have been raised about the use of kill/death ratio as a performance indicator within the esports field. The main consideration is that it favours players who play fewer rounds in a match with fewer deaths will result in a higher kill/death ratio. Kill/death ratio would suggest players had similar performance if player A had 13 kills, 6 deaths (kill/death ratio = 2.17) in a match of 18 rounds and player B had 37 kills, 17 deaths (kill/death ratio = 2.17) in a match of 30 rounds. Interestingly, there were no cases of collinearity between the variables of weekly kills, weekly deaths, weekly kill/death ratio, weekly matches played, and weekly rounds played. Each of the variables of interest measure sufficiently different constructs, which provides evidence to dismiss the consideration that kill/death ratio favours players who play fewer rounds in a match with fewer deaths will result in a higher kill/death ratio. Furthermore, to perform better in the tournaments you need to be a better performer as the better performers in the tournament were also the better players in the lead up to competition. In terms of understanding the attainment of expertise in esports, kill/death ratio offers a simple metric to objectively quantify in-game performance during practice for all expertise levels. However, it is important to note that within team-based environments, each player will have a specific role. For example, an entry fragger plays aggressive and is likely to be eliminated first, which often results in a lower kill/death ratio. Whereas a lurker plays slows and calls out opponents' positions, which often results in a higher kill/death ratio.

Limitations

Inherently, there are limitations present within the study. First, this study did not account for locational or environmental factors that may influence performance. Previously, it has been demonstrated that travel and environmental conditions can either positively or negatively impact performance (Waterhouse, Reilly, Atkinson, & Edwards, 2007). As such, it is possible that prolonged travel may impart a physical and cognitive toll on a player, which may adversely affect performance in competition. Second, performance was only examined in one major esports tournament (PGL Major Krakow 2017). Future research should consider cross-validating these findings in other tournaments and other expertise levels (e.g. semi-professional and amateur esports players) to test the statistical model. Third, data was only collected from each player's main profile. As such, any additional practice on alternative accounts (i.e. smurf accounts – an alternative account used by a known or experienced user in order to deceptively self-present as less experienced) was not accounted for within the present study and would be worthwhile to account for in future research. Furthermore, whether players spent time playing other games during the lead up to competition was not recorded, which may limit the amount of time they have to practice. In addition, the potential of skill transfer from other games (e.g. first-person shooters such as Overwatch and PUBG) remains an area of future research to aim to quantify. Fourth, a large proportion of the variance is also explained by the random effect (team) in this study. This means that a considerable amount of variance is explained by which team the player belongs to, which is reasonable because when a player's teammates obtain kills, it means there are less opponents available to kill the player, and it allows the player to move more easily into favourable positions and obtain subsequent kills themselves. Therefore, team selection was likely the largest contributor to an individual player's tournament performance, hence future research should further explore this interaction. An example of this would be to explore which variables (e.g. interpersonal skills and psychological traits) may be considered in team selection and how these factors may also be related to tournament performance.

Conclusion

This study examined the quantity of practice and in-game performance during practice of professional esports players over an eight-week period in the lead up to a major esports tournament. Overall, the quantity of practice and in-game performance during practice explains a small proportion of the variance in tournament performance. More specifically, the variables that are most associated with better tournament performance are kill/death ratio and score. Interestingly, the quantity of accumulated and weekly practice had limited association with better tournament performance. Although it is likely that practice which is deliberate and purposeful is necessary to reach a high level of expertise in esports, it is apparent that there is more to differentiate between performance than the quantity of practice at the professional level. Therefore, tracking the quantity of practice over a longitudinal period with different expertise levels remains an area for future research.

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All authors listed made a substantial, direct, and intellectual contribution to the work, and approved it for publication. We would also like to acknowledge the help of Mr Tim Schokkaert for his assistance in data collection.

Disclosure statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that would be construed as a potential conflict of interest.

Chapter 8:

Study 6

Examining the quantity of practice of professional and semi-professional esports players: A 52-week longitudinal study

Pluss, M.A., Novak, A. R., Bennett, K. J. M., McBride, I., Panchuk, D., Coutts, A., & Fransen, J. (Prepared for submission). Examining the quantity of practice of professional and semi-professional esports player: A 52-week longitudinal study.

Abstract

This study followed a longitudinal design to examine the practice activities of professional and semi-professional esports players over a 52-week period. Data were collected from 30 male Counter-Strike: Global Offensive players (age: 23.76 ± 2.88 y). Players were a priori classified into two groups: (i) professional (n = 18, age: 23.54 ± 2.99 y) or (ii) semi-professional (n = 12, age: 24.07 ± 2.78 y). The time spent in-game (competitive play and other types of practice) and the time spent in competitive play only were collected weekly. Two Generalised Estimating Equations (GEE) analysed the relationship between the time spent in all types of practice (competitive and non-competitive) and time spent in only competitive play. The GEE with total practice time and total competition practice time as response variables revealed significant associations between practice hours and week (Wald $\chi 2 = 271.2$, $p < 0.001$), and between competitive practice hours and week, (Wald $\chi 2 = 156.01$, $p < 0.001$). The average practice time was 31.2 hours (SE = 1.9 h) per week, whereas the average competitive practice hours was 19.9 hours (SE = 1.6 h) per week. A significant week*group interaction was observed for total practice time (Wald $\chi 2 = 9.48$, $p = 0.002$) and total competition practice time (Wald $\chi 2 = 7.54$, $p = 0.006$). This interaction effect indicates that professional esports players on average accumulate more practice over a one-year period than semi-professional players, of which a large part involves competitive play.

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 (Bányai et al., 2019; Campbell et al., 2018; Hamari & Sjöblom, 2017). The participation in esports has grown rapidly in the last decade and now astonishing, exceeds over 100 million players worldwide (Novak et al., 2020). Anecdotally, much like traditional sports, only a small minority of players compete in professional competition. Despite the limited research on esports expertise, it is possible to draw on and utilise some of our current knowledge from domains such as video games, music, sport, medicine, and academia (Campbell et al., 2018; Dale & Green, 2017; Ericsson, 2006; Ericsson et al., 1993; Leis & Lautenbach, 2020; Pedraza-Ramirez et al., 2020; Starkes & Ericsson, 2003; Thompson, McColeman, Blair, & Henrey, 2019). These domains offer insight into what aspects researchers and practitioners should be interested in when seeking to understanding expertise in esports. A primary area of interest in such expertise research is examining how the practice activities an individual engages in (i.e. the frequency and type of practice) affects the attainment of expertise (Baker et al., 2003; Charness et al., 2005; Côté et al., 2007).

Within many domains, engagement with different types of practice (e.g. deliberate, purposeful, and naïve) affects the level of expertise that an individual attains along with their rate of development (Baker, 2003; Baker et al., 2009; Côté et al., 2003; Ericsson et al., 1993; Ericsson & Smith, 1991; Mattson & Richards, 2010). Some researchers argue that practice has to be deliberate and purposeful to attain expertise (Charness et al., 2005; Ericsson et al., 1993). While, other authors argue that engaging in a wide range of activities, especially at an early age, is beneficial for the development of expertise as an enduring characteristic (i.e. sampling leads to longer careers) (Bridge & Toms, 2013; Goodway & Robinson, 2015). Consequently, researchers have focused on identifying which type of practice is most beneficial for developing expertise (Ericsson et al., 1993). Overall, it is generally accepted that the amount of practice an individual engages in is related to the attainment of expertise across many domains (Ericsson, 2020; Macnamara & Maitra, 2019). Yet, despite its unique window into the development of expertise and the recent increase in studies investigating esports expertise, no research has investigated the relationship between practice and expertise in a cohort of expert esports players (Campbell et al., 2018; Dale & Green, 2017; Pedraza-Ramirez et al., 2020; Pluss et al., 2019; Pluss et al., 2020).

Researchers interested in how practice influences the attainment of expertise often rely on retrospective recall techniques to detail the specific involvements in various activities over prolonged periods (Baker et al., 2018; Côté et al., 2005; Sosniak, 2006). In these studies, participants recall their practice activities over their careers, which can span several decades (Baker et al., 2003; Ericsson, 2015; Jabusch, Alpers, Kopiez, Vauth, & Altenmüller, 2009). However, this approach is influenced by an individual's recall bias and memory recall ability (Howard, 2011). For example, participants generally overestimate the number of practice hours and time since recent milestones and underestimate the number of practice hours and the time since distant ones (Howard, 2011; Kemp, 1988). Given these limitations, an alternative approach is to examine practice longitudinally across development rather than just from a dichotomous viewpoint (Swann et al., 2015). Typically, skilled (e.g. professional and semi-professional) players spend more time in weekly practice when compared with their lesser skilled counter-parts (e.g. amateur and novices) in both individual and team-sport environments (Ericsson et al., 1993; Helsen et al., 1998; Starkes, Deakin, Allard, Hodges, & Hayes, 1996). However, longitudinal data collection on human behaviour can be expensive, time consuming and often requires a large sample size because of poor participant retention (Patel et al., 2003).

Comparatively, esports provides a medium whereby the quantity of practice (e.g. time spent in-game and time spent in competition) and quality of in-game performance (e.g. kill/death ratio, score and most valuable player stars) are objectively tracked and automatically logged online at regular intervals. As such, esports presents a unique perspective to capture a snapshot in time of the development of expertise. Therefore, examining the degree to which players at different performance levels engage in practice throughout a period of development can help improve our understanding about the relationship between practice and performance in this unique context, of which no research evidence currently exists. The present study followed a longitudinal design to examine the quantity of practice of professional esports players and semi-professional esports players over a 52-week period. Following previous work, it was hypothesised that the quantity of practice an esports player engages in would be moderately associated with their current expertise level (Macnamara et al., 2016). Furthermore, it was hypothesised that professional esports players would accumulate more practice over a 52-week period when compared with semi-professional esports players (Ericsson, 2006; Ericsson et al., 1993; Ward et al., 2007).

Methods

Participants

Data were collected from 30 male Counter-Strike: Global Offensive players (age: 23.76 ± 2.88 y). Players were *a priori* classified into two groups: (i) professional (n = 18, age: 23.54 ± 2.99 y) or (ii) semi-professional (n = 12, age: 24.07 ± 2.78 y) based on the level of competition that the player represented on the 1st of January 2017, which was the commencement date for data collection. The professional group involved players that competed on a full-time basis and represented a team at an international level (i.e. major tournaments and world championships) of competition. The professional esports players were from North America (n = 8) or Europe (n = 10). The semi-professional group involved players that compete on a full-time basis and represented a team at a national level (i.e. domestic or regional leagues) of competition. The semi-professional esports players were from North America (n = 4) or Europe (n = 8). The Institutional Ethics Research Committee approved this study.

Experimental procedure

The study used a longitudinal design to examine the quantity of practice of professional and semi-professional esports players over 52-weeks. The two main variables of interest were the *time spent in-game* and the *time spent in competition*. The time spent in-game is a combination of practice that is typically focused on developing individual skills and the time spent in practice in a competitive team-based environment (*time spent in competition)*. The most common type of individual practice is practicing in deathmatch, which is a mode featuring instant respawns (allows players to respawn instantly after death, which is not evident in competition) with the ability to purchase any primary and secondary weapons with no regards to the money economy. Each match lasts 10 minutes and the player with the highest points wins the round. Whereas the time spent in competition involves practice solely in a competitive team-based environment. This type of practice involves two teams consisting of five players competing head-to-head in a 30-round match. The first team to score 16 points wins the game. After 15 rounds (half time), each team switches sides (T-side and CT-side). The T-side must plan C4 at a bombsite and the CT-Side must defend the bombsite. Each round is one minute and 45 seconds long, however, if the T-side team manages to plant the bomb then the round timer resets to 40 seconds. On average, a single competitive match will last approximately 40 minutes, though a competitive match can extend to over an hour if the match is close. If both teams reach 15 rounds each, the game will end in a tie. This study used publicly available data from each player's official Steam® profile and third-party webpages (https://csgo-stats.com and https://www.hltv.org/). The commencement date for data collection was the 1st of January 2017. Furthermore, baseline measures of the accumulated time spent in-game and accumulated time spent in competition was based on the total amount of practice a player engaged in up until the commencement of the study. Following the original data collection date, data were collected at a standardised time on a weekly basis using a custom data scraping method developed in Python, which collated and stored all data into a Microsoft Excel spreadsheet. A labelling rule considered and discarded a data observation as an outlier if they were outside of the value associated with the values derived from multiplying each participants interquartile range (IQR) by 1.5, upon which values beyond the 25th and 75th percentiles ± 1.5 × IQR (Hoaglin & Iglewicz, 1987; Hoaglin et al., 1986). No outliers were identified within the data. Overall, the current study used a total of 3120 observations from 30 participants (two variables for each week per participant).

Statistical analysis

First, two-sided independent samples t-test was used to examine if baseline practice hours at the commencement of this study, total hours spent in-game and total hours spent in competitive practice throughout the experiment were significantly different between professional and semi-professional players. Two Generalised Estimating Equations (GEE) were used to analyse the relationship between practice time (time spent in-game and time spent in competition) (Liang & Zeger, 1986; Zeger, Liang, & Albert, 1988). Generalised Estimating Equations are used to analyse correlated data with different outcomes, such as binary, continuous or discrete (Zeger et al., 1988). Prior to analysis, data was transposed into a long-form data structure, where each row reflects a single week's observation for one player. The presence of non-linear relationships between the independent variables and the response variables was also investigated. While multicollinearity, due to the estimation of populated-averaged effects rather than individual effects is not a strict requirement for using GEEs, interpretation is facilitated when multicollinearity is not present. Therefore, a correlation matrix was used to investigate if multicollinearity was present in the data. A correlation coefficient cut-off of 0.80 was used to determine collinearity between independent variances (Grewal, Cote, & Baumgartner, 2004). If the case of collinearity, the independent variable with the strongest linear relationship with the response variable was retained. The distribution of the response variable was also analysed to specify the correct definition of the variance and link functions of the GEE. In this case the response variable was continuous and followed a normal distribution. As such, a Gaussian distribution with an identity link was specified in the geeglm function in the geepack R package (Halekoh, Højsgaard, & Yan, 2006). The kill/death ratio (number of kills/number of deaths) was transformed into a normalised and standardised z-score to facilitate interpretation. Kill/death ratio is commonly used for statistical analysis purposes to develop online rankings and determining match outcomes. Furthermore, the kill/death ratio of a player was the most significant variable associated with better tournament performance over an eight-week period (Pluss et al., in press). Group (professional and semi-professional), week (weeks 1-52), group*interaction, kill/death ratio, were entered as independent variables. The total hours of practice at baseline was entered as a covariate. A player ID was treated as the clustering variable to account for the clustering of repeated measure of the response variable for a single player. While GEEs are generally robust against misspecifications of the working correlation structure (Liang & Zeger, 1986), the Quasi-likelihood

Information Criterion (QIC) can be used in GEEs to determine an appropriate working correlation structure (Pan, 2001). As a result, three different working correlation structures was compared (exchangeable vs independence vs autoregressive), and the structure that yielded the lowest QIC was retained (Fu, Hao, & Wang, 2018). The model estimated for the two GEEs were derived, and the Wald statistic and p-value were used to analyse if variables added to the model (a significant Wald statistic denotes that a variable adds to the model, a non-significant Wald statistic indicates that this variable can be removed without affecting the model meaningfully. The Variance Inflation Factor (VIF) was used to examine if correlations between the model parameters were observed, with a threshold <5 used to indicate a low correlation. Finally, the final model's residuals were plotted using diagnostics plots to examine systematic errors within the model's predictive ability. The data analysis procedure in this study followed a similar design of Ballinger (2004) when analysing longitudinal data. A criterion alpha level significance was set at $p < 0.05$. All statistical analyses were conducted using R statistical software (R Development Core Team, New Zealand).

Results

Figure 8.1 displays the interaction effects between total hours of practice and total hours of practice in competition for the professional and semi-professional esports players over the 52-week period. Independent samples t-tests revealed significant differences in the total in game hours ($t_{(28)} = 2.79$, $p = 0.001$, 95% CI difference = 83.2 – 551.2, professional: 1603 hrs, semi-professional: 1285 hrs) as well as the total competitive practice hours ($t_{(28)} = 2.54$ $p = 0.018$, 95% CI difference = 44.5 – 434.1, professional: 1019 hrs, semi-professional: 780 hrs) accumulated over the 52-week period. No differences were observed in baseline practice hours between groups ($t_{(28)} = 0.19$, $p = 0.855$). For both response variables, a model with an exchangeable working correlation structure yielded the lowest Bayesian Information Criterion, and as such this working correlation structure was retained. Table 8.1 reports the estimates, standard errors (SE), Wald statistics and associated p-values for both models.

Figure 8.1. The interaction effects between total hours of practice for the professional and semi-professional esports players over the 52-week period.

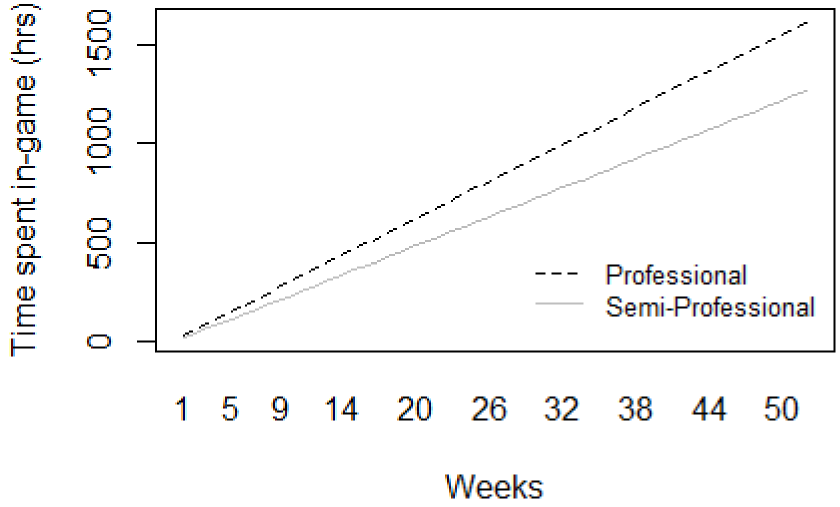

Figure 8.2. The interaction effects between total hours of practice in competition for the professional and semi-professional esports players over the 52-week period.

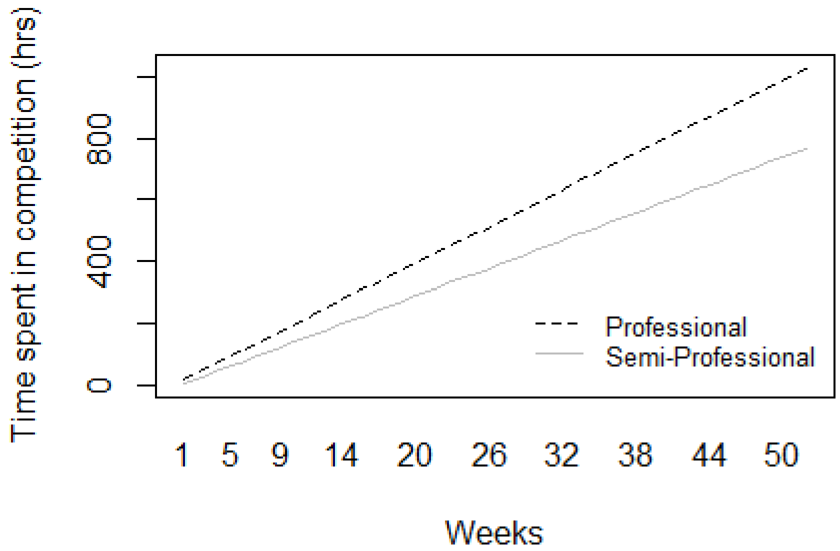

Table 8.1. The coefficient, 95% confidence interval, standard error, Wald statistics and p-values for the two generalised estimating equation models.

Time spent in-game model	**Coefficient**	**95% CI**	**SE**	**Wald χ2**	**p-value**
Intercept	-242.0	-528.0 - 44.3	146.1	2.74	0.098
Group (ref = professional)	-0.1	-46.9 - 46.7	23.9	0.00	0.997
Week	31.2	27.5 - 35.0	1.9	271.20	<0.001
Baseline practice hours	0.04	-0.01 - 0.09	0.03	2.42	0.120
Kill/death ratio	-7.1	-60.5 - 46.2	27.2	0.07	0.794
Group*week	-6.6	-10.9 - -2.4	2.2	9.48	0.002
Time spent in competition model	**Coefficient**	**95% CI**	**SE**	**Wald χ2**	**p-value**
Intercept	-358.0	-586.0 - -148.0	107.2	11.15	0.001
Group (ref = professional)	-2.0	-53.6 - 49.6	26.3	0.01	0.940
Week	19.8	16.7 - 22.9	1.6	156.01	<0.001
Baseline practice hours	0.06	0.02 - 0.99	0.02	10.16	0.001
Kill/death ratio	-8.6	-47.5 - 30.2	19.8	0.19	0.663
Group*week	-4.8	-8.2 - 1.4	1.8	7.54	0.006

Note: CI: confidence interval, SE = standard error.

Effects on total time spent in-game

The GEE with total practice time as a response variable revealed significant associations between practice hours and week (Wald $\chi2 = 271.2$, $p < 0.001$). The sample in this study spent on average 31.2 hours (SE = 1.9 h) in practice per week. No significant relationship was observed between kill/death ratio and practice time (Wald $\chi2 = 0.07$, $p = 0.794$) or baseline practice hours at the onset of data collection and total practice hours (Wald $\chi2 = 2.24$, $p = 0.120$). Finally, while no significant differences in practice time were identified between professional and semi-professional at the commencement of data collection (Wald $\chi2 = 0.00$, $p = 0.997$), a significant week*group interaction effect was observed (Wald $\chi2 = 9.48$, $p = 0.002$). This interaction effect indicates that professional players accumulated more practice on a weekly basis. Collectively, they accumulated 6.6 hours (SE = 2.2 h) more every week throughout the study. No parameters had VIFs larger than five, concluding no correlation between the parameters in the model.

Effects on total time spent in competition

The GEE with total competition practice time as a response variable revealed significant associations between competitive practice hours and week (Wald $\chi2 = 156.01$, $p < 0.001$). The sample in this study spent on average 19.9 hours (SE = 1.6 h) in competitive practice per week. An association was also found between the total practice hours at the onset of data collection and competitive practice hours throughout the following 52 weeks (Wald $\chi2 = 10.16$, $p = 0.001$) where with each hour of accumulated practice a player had at baseline, a 3.6 min (SE = 1.2 min) increase in competitive practice time was revealed. No significant relationships between playing level and competitive practice hours (Wald $\chi2 = 0.01$, $p = 0.940$) or between kill/death ratio and competitive practice time were identified (Wald $\chi2 = 0.19$, $p = 0.662$). The GEE did reveal a week*group interaction effect (Wald $\chi2 = 7.54$, $p = 0.006$). This interaction effect indicates that every week, the sample of professional players accumulate an additional 4.8 hours (SE = 1.8 h) in competitive practice. Two parameters had VIFs larger than five (week = 6.41 and group*week = 5.56 indicating moderate correlations between these two parameters in the model). The diagnostics plots (residuals vs fitted and qqplots) demonstrated that both models tended to overestimate low practice times, and underestimate high practice times.

Discussion

The current study examined professional and semi-professional esports players quantity of practice over a 52-week period. Baseline measures of practice did not significantly differ between the professional and semi-professional groups. The overall amount of practice and the practice in competitive environments accumulated throughout the study was significantly greater for the professional than semi-professional players. Furthermore, the professional group accumulated an additional 6.6 hours of practice on a weekly basis, of which 4.8 hours are spent in competitive practice compared with the semi-professional group. Overall, this resulted in a mean accumulated practice time that is on average 318 hrs (95% CI: 83 - 551 hrs) greater for professional than semi-professional players over a 52-week period.

The findings of this study also identified that commonly used performance metrics such as kill-death ratio or performance ratings (i.e. HLTV rating – a tool that can be used to objectively examine a player's performance) are not associated with the amount of time esports players engage in different type of practice. The latter findings are similar to those of Pluss et al. (in press) who demonstrated that the weekly quantity of practice over an eight-week period in the lead up to a major esports tournament had limited association with tournament performance in professional esports players. However, it is important to note that professional esports players have more time available to practice, it does not necessarily mean that they reached their current level by practicing more. Perhaps for relatively homogeneous populations, performance metrics may not be directly associated with practice quantity and that there is more to differentiate between performance than the quantity of practice. In addition, Novak et al. (2020) suggested that more sophisticated models (i.e. structural equation modelling and path analyses) are needed to truly capture how key performance indicators are associated with esports performances. Therefore, future longitudinal studies should also record the quantity of practice and quality of in-game performance at the smallest unit of analysis, rather than using average values over the duration of the study. Recording data at the smallest unit of analysis will provide a more in-depth understanding about the relationship between practice and performance in esports.

Examining the amount of practice at intervals over a period of time provides researchers a snapshot in time of the development of expertise and the practice activities individuals engage in as they develop expertise (Williams & Ford, 2008; Williams et al., 2012). Over the 52-week period, expert esports players engaged in practice focused on developing individual skills (e.g. deathmatch) and practice in a competitive team-based environment (e.g. competition) for an average of 31.2 hours per week (SE = 1.9 h), whereby an average of 19.9 hours (SE = 1.6 h) were spent in competition. Similar practice history profiles have been reported in expert violinists, who practice on average 26.7 hours per week (Ericsson et al., 1993). Furthermore, international-level wrestlers estimated spending 38.7 hours per week compared to club level wrestlers who practiced 20.9 hours per week (Starkes et al., 1996). Whereas in team sport athletes, national and international soccer players spend on average 13.3 and 9.9 hours per week in combined individual and team practice, respectively. In comparison, less skilled players accumulated only 6.9 hours in practice per week. Similarly, in field hockey international and national players spend on average 10.5 and 7.5 hours per week, respectively, in team practice compared with 3.7 hours per week for the provincial level players (Helsen et al., 1998). Overall, expert esports players have a similar practice history profile with other individual-based domains, but spend more time in practice compared with experts in some other team-based domains (Ericsson et al., 1993; Starkes et al., 1996).

Professional and semi-professional esports players accumulate practice at a much greater rate than those reported for athletes in other team-based sports, such as soccer and hockey (Helsen et al., 1998). Assuming professional and semi-professional esports players practice the same amount for every year, extrapolating the data over a 10-year period would suggest esports players of relatively high-expertise levels accumulate more than 16,200 hours of practice. Previously, international, and national soccer players have respectively accumulated on average a total of 9,332 ± 223 and 7,449 ± 268 practice hours at 18 years into their career (Helsen et al., 1998). Similarly, international, and national field hockey players have respectively accumulated on average a total of 10,237 ± 980 and 9,147 ± 805 practice hours at the same stage of their career (Helsen et al., 1998). As such, expert esports players would invest the same amount of time in practice when compared with other expert athletes in team-based esports in less than half the time. Perhaps the large amount of time invested into practice is one of the main contributing factors underlying the high burnout rate associated in esports (García-Lanzo & Chamarro, 2018; Salo, 2017). However, these practice hours are likely to be higher given the virtual nature of practice not requiring physical proximity and substantive physical effort. Furthermore, it is important to note that the diagnostics plots (residuals vs fitted and qqplots) demonstrated that both of the GEEs tended to overestimate low practice times and underestimate high practice times. As such, it is recommended that the GEE models should not be used for prediction, and the previous extrapolation purely serves an illustrative purpose. The GEEs in this study should only be used for explanatory purposes, which can be useful to describe which factors are associated with practice in esports. Furthermore, the authors encourage researchers to utilise the supplementary material (i.e. the R code for reproducing the statistical analysis and full dataset) provided for future reproducibility purposes.

Inherently, there are limitations present within the study. First, the present study used average values over the duration of the study, rather than recording the quality of in-game performance (kill/death ratio and score) at the smallest unit of analysis. Recording data at the smallest unit of analysis would have improved the explanatory power within the GEE models. Secondly, another consideration when recording time spent in-game (not applicable to time spent in competition) is idle time. As a rule, time spent in-game includes the entire duration which the game is running, regardless of whether the player is playing it. Therefore, idle time includes when players are not actively practicing and may include time spent waiting in matchmaking queues, doing other non-game related tasks, or even leaving the computer on while unattended. Anecdotally, players have acknowledged in interviews how their total time spent in-game is often inflated by idle time and this presents a potential confound to time spent in-game. However, idle time in esports is not an uncommon phenomenon and its contribution to total practice time far exceeds that of any interstitial waiting time of an association football player “waiting” on the pitch. It may be more equivalent to the travel time to and from practice facilities as part of practice time. Overall, it is worthwhile to address as it is very difficult to control for given the methods used in the present study, and it is likely that all players have some degree of idle time, even if it is difficult to measure. Thirdly, as the *a priori* classification of expertise group was based on the players current competitive status on the commencement date of data collection (1st of January 2017). Any situations where players move from team to team during the year and how this may influence practice was not accounted for within the present study. Fourthly, the quantity of practice was only examined over one competitive year (2017). Future research should consider cross-validating these findings for other years and over longer periods of time to test the statistical models. Lastly, data was only collected from each player's main profile. As such, any additional practice on alternative accounts was not accounted for within the present study.

Conclusion

The current study examined the practice activities of professional and semi-professional esports players over a 52-week period. Baseline measures of practice did not significantly differ between the professional and semi-professional groups, but professional esports players on average accumulate more practice over a one-year period than semi-professional players, of which a large part involves competitive play. Furthermore, the findings of this study also identified that commonly used performance metrics such as kill-death ratio or performance ratings are not associated with the amount of time esports players engage in different types of practice. Overall, this study provides new insights into the quantity of practice a professional and semi-professional esports players engages in over a competitive year, which can complement the current understanding about the association between practice and expertise.

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Disclosure statement

The authors declare that the research was conducted in the absence of any commercial or financial relationships that would be construed as a potential conflict of interest.

Chapter 9:

General discussion

Thesis summary

The present thesis contains a series of studies in esports, an emerging domain which offers researchers an opportunity to overcome some of the current issues associated with assessing the characteristics of an expert and studying the development of expertise in more traditional domains (Study 1). When assessing the characteristics of experts, perceptual-motor abilities may underlie expertise in esports, yet their ability to distinguish between professional and recreational esports players is limited (Study 2). Given that performance in the speed-accuracy trade-off task was the main distinguishing factor between expertise levels, computerised speed-accuracy trade-off tasks have value as an esports-specific performance measure (Study 3). Furthermore, given expert performance is maximised under conditions that more closely replicate the performance context, Study 2 and Study 3 highlighted the importance of using computer-based assessments to conduct domain-specific investigations to understand the characteristics of experts in esports. However, it appears that esports perceptual-motor skills remain difficult to quantify and further research is needed to develop valid and reliable assessments (Study 4).

In terms of studying the development of expertise, Study 5 and Study 6 explored the association between practice and expertise in professional and semi-professional esports players' performance. While deliberate and purposeful practice is undoubtedly necessary to reach a high level of expertise in esports, it is apparent that practice quality may be important to distinguish between performance levels in a homogeneous group of professional esports players (Study 5). Furthermore, professional esports players on average accumulate more practice over a one-year period than semi-professional players, of which a large part involves competitive play (Study 6). Overall, these findings supports that the development of expertise is subject to similar positive relationships between

practice and performance revealed in other domains of expertise and highlights that sufficient practice time may be an important contributor to the attainment of expertise. However, once players reach expert levels, the quality of practice might be a largely contributing factor to performance rather than the quantity of practice. Collectively, the implications of these findings are further discussed below.

Assessing the characteristics of an expert in esports

As expert performance is maximised under conditions that more closely replicate the performance context (Farrow et al., 2018; Pinder et al., 2015). Currently, the main issue with assessing the characteristics of an expert is the challenges associated with developing tasks that accurately capture performance under specific task constraints that effectively reflects the functional responses of performers in situations that represent performance (Ericsson & Lehmann, 1996; Helsen & Starkes, 1999; Williams & Ericsson, 2005). The main advantage with assessing the characteristics of an expert in esports is that 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).

Study 2's findings indicated that some perceptual-motor abilities may underlie expertise as they can discriminate between professional esports players and a control group. However, their ability to distinguish between professional and recreational esports players is somewhat limited. Overall, professional esports players produce shorter movement times and are more likely to adapt their movement time to changes in task difficulty (under accuracy constraints) in a computerised speed-accuracy trade-off task when compared with recreational esports players and a control group. Given human-computer interactions mediates esports performance, 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 (Kowal et al., 2018). As esports players are required to click back and forth between targets at a fast pace with high accuracy during performance, it is likely that a computer-based assessment would distinguish between expertise groups. Therefore, it is also likely that assessing the characteristics of experts in esports is also maximised under conditions that more closely replicate the performance context (Farrow et al., 2018; Pinder et al., 2011).

Another finding from Study 2 is that professional esports players 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 compared to recreational esports players. 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. These findings provide support that experts esports players have similar information processing abilities to other experts in domains like sport which also demonstrate shorter faster response times when compared with individuals with no sporting background, but minimal differences when compared with lesser skilled athletes (Mann et al., 2007; Voss et al., 2010).

Anecdotally, this may be because esports players typically identify and process task-relevant information, auditory information from the in-game environment, and team communications, whereby in doing so they reduce the number of choices they will be required to respond to at any given time. For example, in first-person shooters like Counter-strike: Global Offensive, esports players use contextual information (i.e. last known location of an enemy, auditory information about the location of an opponent, and prior game knowledge of the opponent's playstyle) to make an informed decision on a small number of reasonable options that an enemy is likely to appear within the environment, which allows for faster response times based on anticipating the enemies' intentions.

Study 2's findings also documented that professional esports players were less 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 provides support for the facilitating effect of congruent precues and the limiting effect of incongruent precues has on expert esports players, which is also a characteristic of experts from other domains (Barela et al., 2019; Beavan et al., 2019; Bugg & Diede, 2018; Chiew & Braver, 2016; Posner, 1980). Perhaps professional esports players have a superior ability to utilise relevant visual cues (i.e. information where a stimulus is going to appear such as an enemies gun appearing from behind an object immediately prior to their body) and quickly disengage from irrelevant visual cues (i.e. incorrect information where a stimulus is going to appear such as an irrelevant object appearing on one side of the screen immediately prior to an enemy appearing on the other side of the screen) in the environment.

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. Despite no differences between professional and recreational esports players, this 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 generally. Overall, it highlights that certain perceptual-motor abilities may be useful to distinguish between esports players and controls with no experience in esports. However, some perceptual-motor abilities have limited ability to distinguish those with high levels of expertise from those with moderate levels of expertise (Beavan et al., 2020; Beavan et al., 2019). Like the evidence reported in other domains, these findings provide support that it is likely that domain-general abilities may be foundational to the development of expertise in esports (Hambrick et al., 2019; Mann, Abernethy, & Farrow, 2010; Roberts, 2008).

Given that performance in the speed-accuracy trade-off task was the main distinguishing factor between expertise levels (Study 2), a more detailed analysis was warranted (Study 3). Although movement time increased linearly with the ID for each group, overall the professional esports players displayed the shortest movement times for each ID when compared with the recreational group and control group. However, there were minimal significant differences in movement time between the conditions where the distance between the targets remained the same, but the width of the targets was half the size, in the recreational (only ID 3^A and ID 3^B) and control (no significant differences) groups. Interestingly, there were several significant differences in mean movement time for the professional group between the conditions where the distance between the targets remained the same, but the width of the targets decreased by half (except for ID 2^A and 2^B).

Evidently, the movement time of the control group is generally not affected by changes in the target distance and target width, even when increasing target distance and reducing target width. As the movement time of the control group remained unaffected in the majority of the conditions, it appears that the control group do not decrease movement time to maintain accuracy. In other words, the control group do not adapt to the imposed accuracy demands of the task. In the recreational group, increasing target distance and reducing target width did affect movement time in some cases. The movement time of the recreational group was most affected in conditions where the target distance remained the same, but the target width was halved. Therefore, the recreational group adapted to the imposed accuracy demands of the task, however this was only to some extent. Yet, the professional group demonstrated the most adaptability to the imposed accuracy demands of the task, given a change in target distance or target width would almost always lead to changes in movement time, except in one condition where the index of difficulty is relatively low. Overall, professional esports players produced shorter movement times and are also more likely to adapt their movement time to changes in task difficulty with imposed accuracy demands when compared with recreational esports players and a control group. Collectively, these findings provide support that in manual aiming skills, experts demonstrate shorter movement times when tasks constraints are imposed on performance when compared with novices (Proteau, 1992; Proteau & Marteniuk, 1993; Proteau et al., 1992).

Another finding from Study 3 is that the effect sizes associated with a linear relationship between movement time and ID were similar for each group, however the effect sizes associated with a quadratic relationship between movement time and ID were greatest in the professional group. Evidently, the relationship between ID and movement time in the professional group changes more rapidly once the ID of a task reaches a threshold, which in the case of the current study was between ID 3^B to ID 4^A. After this threshold has been exceeded, it appears that the movement time of the professional group will increase more rapidly when compared with the recreational group and the control group. This may reflect that with certain accuracy demands, professional esports players are more sensitive to changes in conditions after the ID has exceeded a certain threshold.

Anecdotally, a common characteristic in first-person shooters (e.g. Counter-strike: Global Offensive, Overwatch, and PUBG), and multiplayer online battle arenas (e.g. League of Legends and Heroes of the Storm) esports players is that they typically maintain the position of the cursor in areas of relative importance (e.g. likelihood of areas where the opponent may appear) as it will likely result in more successful outcomes of performance (e.g. winning the objective, eliminating the opposition). Given the position of the cursor is close to the areas of importance, there are several benefits this may have on performance: i) there is less distance to move when a stimulus appears, which likely decreases the likelihood of movement errors, ii) it allows the ability to prepare the action when required iii) reduces the potential influence of the speed-accuracy trade-off. Perhaps this is a potential explanation as to why the movement time of the professional group was slower when the imposed accuracy demands increased. It is likely that lower IDs reflect the movements that would typically characterise esports performance, whereas the higher IDs reflect the movements that would be observed in rare instances were an esports player has not maintained the position of their cursor in areas of relative importance. Given higher IDs reflect the movements that typically would not characterise esports performance, these findings support other research that suggests that experts will outperform novices in tasks they are familiar with, however performance differences are less likely to be evident in tasks that do not accurately replicate the behavioural characteristics that would be observed in performance (Adams et al., 2013; Seamster et al., 2000).

Given the practicality and use of computer technology in esports, it was concluded that future research should incorporate more domain-specific measures (i.e. computer-based assessments) of performance when assessing the characteristics of experts in esports. Therefore, Study 4 investigated the test-retest reliability and construct validity of a commonly used esports perceptual-motor skill assessment (Mobalytics Proving Ground Test) using an expert/non-expert paradigm. Although the current study incorporated an assessment that should more readily reflect the demands of esports performance (i.e., a commonly used task developed to assess and train League of Legends players), many of the variables obtained from this task were not associated with esports expertise (Ericsson & Lehmann, 1996; Pinder et al., 2015). This finding is likely the result of the reduced specificity in the perception-action coupling of aspects of the assessment (Hadlow et al., 2018).

Overall, players are not required to execute specific actions appropriate to the imposed task demands of League of Legends within the Mobalytics Proving Ground Test assessment. This indicates that even when an esports perceptual-motor skill assessment is practically relevant and may appear to have sufficient face-validity for measuring domain-specific performance in League of Legends, it may not be necessarily useful for assessing the characteristics of expert esports players. Furthermore, while this specific assessment is designed as an assessment and training tool for esports performance, it clearly lacks task representativeness, and therefore it is advised not be used in the study of esports expertise. Similar to the difficulties that researchers are faced with when developing representative tasks to assess expertise, this finding provides support that esports-perceptual-motor skill assessments that decouple the perception and action processes and use poor information sources are also likely to be limited in their ability assess the characteristics of an expert (Brunswik, 1956; Pinder et al., 2011; Pinder et al., 2015).

Therefore, it is important when designing assessments aimed at quantifying performance characteristics in esports to incorporate specific task goals and actions that accurately replicate the task demands of competition. As such, researchers interested in exploring expertise in esports, particularly in League of Legends, should aim to utilise technology that allows for the measurement of player performance in-game (i.e. the practice tool in League of Legends is a mode specifically designed to allow players to interact with training dummies), rather than designing external assessments that do not require players to use game-specific actions to respond to game-specific information in a way that replicates their actions during competitive play.

Studying the development of expertise in esports

One of the main issues with studying the development of expertise, is that researchers often rely on using retrospective methods or limited by resources to accurately examine the learning history of an individual over a period of time (Baker et al., 2003; Baker et al., 2003; Baker et al., 2018). The main consideration with using retrospective methods is that the validity and reliability of the data is often shaped by the memory recall ability of an individual (Baker et al., 2018; Côté et al., 2005; Howard, 2011). The main advantage with studying the development of expertise in esports is that it provides a medium whereby the quantity of practice and quality of in-game performance are objectively tracked and automatically logged online at regular intervals (Pluss et al., 2019).

Study 5's findings indicated that the quantity of practice and in-game performance during practice over an eight-week period in the lead up to competition explains a small proportion of the variance in tournament performance in Counter-Strike: Global Offensive. More specifically, the variables that are most associated with better tournament performance in Counter-Strike: Global Offensive are kill/death ratio and score during the lead up to competition. In terms of understanding the attainment of expertise in Counter-Strike: Global Offensive, kill/death ratio offers a simple metric to objectively quantify in-game performance during practice for all expertise levels. However, it is important to note that within team-based environments of Counter-Strike: Global Offensive, each player will have a specific role. For example, an entry *fragger* plays aggressively and is likely to be eliminated first, which often results in a lower kill/death ratio. Whereas a *lurker* plays slow and calls out opponents' positions, which often results in a higher kill/death ratio. Furthermore, whether kill/death ratio and score can be generalised as a useful metric to objectively quantify in-game performance for other similar first-person shooters (e.g. Overwatch and Tom Clancy's Rainbow Six Siege, among others) remains an area for future research.

Another finding from Study 5 is that the quantity of accumulated and weekly practice had limited association with better tournament performance. Although it is likely that practice which is deliberate and purposeful is necessary to reach a high level of expertise in esports, it is apparent that there is more to differentiate between performance than the quantity of practice in a homogeneous group of professional esports players. As such, this finding provides support that the amount of practice an expert engages in during the lead up competition has limited associated with better performance (Macnamara & Maitra, 2019; Young, 1998). Given that professional esports players compete on a full-time basis and represent a team at an international level (i.e. major tournaments and world championships) of competition, it is likely that the amount of practice a professional esports player engages in during the lead up to a major esports tournament is similar, and therefore may not distinguish between performance at the highest level of competition in Counter-Strike: Global Offensive.

Anecdotally, this is likely because during the lead up competition, professional esports players will travel to the location of the tournament in the preceding weeks and complete a boot camp (i.e. learn new skills, train as a team, and prepare strategies). During this time, one of the main forms of practice that a professional esports player will engage in is organised scrimmages, which is an informal match against other professional teams that are often competing in the same upcoming tournament. As scrimmages require an individual to practice within their respective team, it is likely that majority of practice will be shared among professional esports players. Whether this is the most effective form of practice to engage in during the lead up to competition tournaments in esports remains an area for future research.

Furthermore, a considerable amount of variance is explained by which team a professional esports player belongs to. This finding makes sense as when a player's teammates obtain kills, it means there are fewer opponents available to kill the player, and it allows the player to move more easily into favourable positions and obtain subsequent kills themselves. Therefore, team selection was likely the largest contributor to an individual player's tournament performance, hence future research should further explore this interaction given team selection has been identified as the best predictor of performance within other team-based environments (e.g. basketball, soccer, cricket, and baseball) (Mukherjee, Huang, Neidhardt, Uzzi, & Contractor, 2019). Following previous expertise research, an example of this would be to explore which variables (e.g. interpersonal skills and psychological traits) may be considered in team selection and how these factors may also be related to tournament performance (Burgess & Naughton, 2010; Casolino et al., 2012; Connerley & Mael, 2001).

Whether the quantity of practice distinguishes between performance levels of professional esports players in comparison to lesser skilled esports players (e.g. semi professional and amateur) remained an area for future research. Therefore, Study 6 examined the quantity of practice of professional esports players and semi-professional esports players in Counter-Strike: Global Offensive over a 52-week period. Overall, professional esports players on average accumulate more practice over a one-year period than semi-professional players, of which a large part involves competitive play. However, it is possible that professional esports players have more time available to practice, it does not necessarily mean that they reached their current level of expertise by practicing more.

This finding provided support that expert esports players in Counter-Strike: Global Offensive have a similar practice history profile, or even spend more time in practice, compared with experts in some other domains of expertise, such as sport, chess, and music

(Ericsson et al., 1993; Starkes et al., 1996). Furthermore, this supports that esports expertise in Counter-Strike: Global Offensive is subject to similar positive relationships between practice and performance revealed in other domains of expertise and highlights that sufficient practice time may be an important contributor to the attainment of expertise in esports (Baker et al., 2003; Baker et al., 2003; Baker et al., 2018; Ward et al., 2007). Whether this is the case for other esports titles remains an area for future research given the number of experts can vary depending on the popularity of the game itself (i.e. thousands of professional esports players in League of Legends and Counter-Strike: Global Offensive compared with the hundreds of professional esports players in Overwatch and Rainbow Six Siege) (Khromov et al., 2019).

Interestingly, another finding from Study 6 is that professional and semi-professional esports players in Counter-Strike: Global Offensive, which is a team-based esports, accumulate practice at a much greater rate than reported for athletes in other team-based sports, such as soccer and hockey (Helsen et al., 1998). When extrapolating the data over a 10-year period would suggest esports players of relatively high-expertise levels accumulate more than 16,200 hours of practice. As such, over the same time period, expert esports players would invest more than twice as much time in practice when compared with other expert athletes in team-based sports. However, these practice hours are likely to be higher given the virtual nature of practice not requiring physical proximity, substantive physical effort, or moving to a different location just to practice (e.g. the training pitch or the sports hall). Furthermore, competitive practice is significantly facilitated in esports given the global, virtual nature of the discipline itself. As such, an esports player who wants to practice can find willing opponents with a similar skill level at any time of day through the engagement in online matchmaking services.

Overall, this study demonstrates that expert esports players have a similar practice history profile, or even spend more time in practice when compared with experts in some other domains. Despite this, perhaps the large amount of time invested into practice is one of the main contributing factors underlying the high burnout rate associated in esports (García-Lanzo & Chamarro, 2018; Salo, 2017). Although many highly skilled esports players burnout and retire at a young age (i.e. typically between the ages of 20 years and 30 years), it opens up avenues for transferring the skills an esports player acquires over time to other domains that require human-computer interaction (e.g. air traffic leaders, surgeons, and medical personnel) (Bavelier et al., 2011; García-Lanzo & Chamarro, 2018). This notion is gaining traction as defence forces around the globe are currently seeking to recruit esports players to operate certain technologies and machinery, whereby soldiers send inputs to computers through electromechanical pointing devices (e.g. mouse, touchpad, and track point) and receive outputs on visual displays (e.g. computer monitor) (Mead, 2013; Sparrow, Harrison, Oakley, & Keogh, 2018).

Limitations

While the specific limitations of each study are presented in their respective chapters, there are some limitations that apply to the overall findings of the thesis. First, players were recruited from a small sample within New South Wales for studies 2, 3, and 4. Despite retaining a level of homogeneity within the sample, the findings are not representative of the entire population of Oceania (e.g. Australasia, Melanesia, Micronesia, and Polynesia) esports players and the overall population of more top performing regions (e.g. North America, Europe, and Korea). The region of Oceania is typically less successful at an international level of competition, contains a relatively smaller talent pool, limited by financial and logistical resources, and have a weaker domestic competition compared with more top performing regions. However, players were recruited from a relatively small sample within top performing regions (i.e. North

America and Europe) for studies 5 and 6. As such, the findings are not representative of the entire population of professional esports players from other regions. Given Study 5 and 6 utilised data scraping methods to collect publicly available data of a player's profile, the accuracy of the data cannot be ensured. While we used data wrangling methods to examine each data set in detail, whether the raw data that makes up these datasets is correct is difficult to ascertain. For example, idle time involves esports players that are not actively practicing and may include time spent waiting in matchmaking queues, doing other non-game related tasks, or even leaving the computer on while unattended and can often inflate time spent playing the game itself. Although the contribution to total practice time far exceeds that of any interstitial waiting time of an association football player "waiting" on the pitch. It may be more equivalent to the travel time to and from practice facilities as part of practice time. Overall, it is worthwhile to address as it is very difficult to control for given the methods used in studies 5 and 6, and it is likely that all players have some degree of idle time, even if it is difficult to measure. Furthermore, access to publicly available data of expert esports players is becoming less accessible as the professionalism of esports continues to increase. Therefore, the authors encourage esports to follow traditional monitoring approaches by embedding researchers within professional teams to collect data at the highest level of competition. Second, as study 2, 3 and 4 are cross-sectional analyses, it is only possible to associate the characteristics related to expertise in esports, therefore the practical implications warrant further verification. For example, researchers can longitudinally track the characteristics related to expertise in esports, which will allow for retrospective analyses of esports players who attain expert status in esports. Third, as with most of the expertise research, it assumed that all players provided a maximal effort throughout the data collection process. Therefore, a players' motivational levels may affect the observed findings. As such, future research should consider using visual analogue scales to quantify the perceived efforts of esports players during assessments. Fourth, prior night's sleep and the time of day of the assessments (circadian effects) were not recorded throughout the data collection process. Sleep loss has a measurable impact on performance through decreases in cognitive functions and effects on biological pathways that support cognitive performance (Fullagar et al., 2015; Krueger, 1989; Waters & Bucks, 2011). Therefore, future research should consider routine screening of sleep as part of the cognitive assessment. Fifth, as esports is a relatively new domain and the current pool of expert players emerged without the influence of guided systematic training environments at the time of preparing the thesis. Since then, higher-level teams have access to experienced coaches and online coaching platforms (e.g. scope.gg, gamer sensei and better gamer) available to esports players to train systematically. Therefore, it is possible that in the following years that expert esports players may have a different skillset and developmental pathway compared with the current pool of expert esports players recruited within the studies of the thesis.

Practical implications

From the findings in the present thesis, several practical implications are derived for expertise research, which complements our current understanding about the assessment and development of expertise. While these findings are discussed from the perspective of esports, some of these implications are still applicable to other domains of expertise.

- Domain-general abilities may be foundational to the development of expertise but have limited ability to distinguish professional esports players compared with recreational esports players.
- A computerised speed-accuracy trade-off task appears to have value as an esports-specific performance measure as it discriminates between expertise level in esports players, as well as distinguishing esports players from controls with no mentionable esports experience.

- When designing esports perceptual-motor skill assessments, it is imperative that the perception-action coupling used in the assessments closely resembles those used in competition.
- Kill/death ratio offers a simple metric to objectively quantify in-game performance during practice for all expertise levels in Counter-Strike: Global Offensive, yet it should not be used to predict competitive performance.
- Investing a large amount of time into deliberate and purposeful practice is likely necessary to develop expertise in esports, and for aspiring players to remain competitive.
- Although esports-perceptual motor assessments are practically relevant, and prevalent in professional esports practice, it does not necessarily mean it is a reliable and valid assessment.
- Esports coaches should be aware that an excessive amount of practice an individual engages in the lead up to competition is unlikely to lead to better tournament performance.
- Esports coaches should monitor a player's performance in the lead up to competition, as the better performers in tournaments are also the better players during training in the preceding weeks.

Chapter 10:

Summary and recommendations

Thesis summary

Study 1 provided an insight into how esports is a modern domain that can be used by researchers to improve our knowledge about expertise in humans. Study 1 was the first theoretical paper to highlight the opportunities that esports offers researchers interested in assessing the characteristics of an expert and studying the development of expertise. The following three studies (Study 2, 3 and 4, respectively) were focused on assessing the characteristics of an expert, whereas the last two studies (Study 5 and 6) were focused on studying the development of expertise in esports.

In terms of assessing the characteristics of an expert, Study 2 described that some perceptual-motor abilities may underlie expertise in esports, yet their ability to distinguish between professional and recreational esports players is limited. Given that performance in the speed-accuracy trade-off task was the main distinguishing factor between expertise level in Study 2, a more detailed analysis was warranted (Study 3). Study 3 demonstrated that professional esports players produce shorter movement times and adapt their movement time to changes in task difficulty with imposed high accuracy demands when compared with recreational esports players and a control group. Furthermore, given the practicality and use of computer technology in esports, Study 3 highlighted that future research should incorporate computer-based assessments when assessing expertise in esports. Therefore, Study 4 examined the test-retest reliability and construct validity of a commonly used esports perceptual-motor skill assessment using an expertise paradigm. Overall, the esports perceptual-motor skill assessment used in the current study can discriminate between an esports player and a control group to some extent. However, the assessment has limited applicability when aiming to quantify some of the performance characteristics of an esports player. The removal of key contextual information and a lack of any clear or meaningful objective seems to limit the test-retest reliability and construct validity of the task. Therefore, when assessing the characteristics of experts in esports, it is important when designing assessments aimed at quantifying performance characteristics to incorporate domain-specific measures, specific task goals and actions that accurately replicate the task demands of competition. Additionally, this study demonstrates that just because an assessment is practically relevant, and prevalent in professional esports practice, it does not necessarily mean it is a reliable and valid assessment.

In terms of studying the development of expertise, Study 5 and Study 6 explored the association between practice and expertise in professional and semi-professional esports players' performance. Study 5 was the first to show the association between practice time and performance, and subsequent tournament performance in professional esports players. Study 5 highlighted that while deliberate and purposeful practice is undoubtedly necessary to reach a high level of expertise in esports, it is apparent that practice quantity alone does not distinguish between performance levels in a homogeneous group of professional esports players. As a result, whether the quantity of practice distinguishes between performance levels of professional esports players in comparison to lesser skilled esports players (e.g. semi professional and amateur) remained an area for future research. Therefore, Study 6 examined the quantity of practice of professional esports players and semi-professional esports players over a 52-week period. Overall, professional esports players on average accumulate more practice over a one-year period than semi-professional players, of which a large part involves competitive play (Study 6). This supports that the development of expertise is subject to similar positive relationships between practice and performance revealed in other domains of expertise and highlights that sufficient practice time may be an important contributor to the attainment of expertise. However, perhaps the large amount of time invested into practice is one of the main contributing factors underlying the high burnout rate associated in esports (García-Lanzo & Chamarro, 2018; Salo, 2017).

Future research directions

While the overall findings from this thesis are promising, it is essential that further comprehensive studies are conducted to further complement our current understanding about the assessment and development of expertise in esports. Some recommendations for future research include:

1. The strategies used by esports players in a computerised speed-accuracy trade-off task

Study 3 explored Fitts' law with a computerised speed-accuracy trade-off task adapted from the original task developed by Fitts' (1954) in esports players using an expert/nonexpert paradigm. Although professional esports players displayed significantly shorter movement times when compared with recreational esports players and the control group, professional esports players produce shorter movement times and adapt their movement time to changes in task difficulty with imposed high accuracy demands when compared with recreational esports players and a control group. Based on the study's findings, future research is required to understand the distribution of responses and the strategies adopted by esports players in a computerised speed-accuracy trade-off task. Understanding the distribution of responses (i.e. a more sensitive measure of exact response accuracy) can provide a valuable insight into identifying the strategies an esports player uses to refine their movements. For example, if a player has a large variable error (the standard (+ or -) deviation from the target), the result of their performance can be compensated with slight adjustments. Whereas, if a player has a large variable error, it will require further development and refinement. As lower variable error is more favoured for goal-directed movements, it is likely that professional esports player demonstrate this characteristic.

2. Visual search strategy, selective attention, and expertise in esports performance

Although the esports perceptual-motor skill assessment used in Study 4 can to some extent discriminate between an esports player and a control group, the reliability and validity of the assessment remains disputed. One of the main issues of the assessment is that it lacked test-retest reliability and there was a lack of stability of different performance measures within the task across multiple trials. The likely reason for this finding is due to the nature of the objective associated with the assessment as it was rather arbitrary, whereby performance across the tasks may be influenced by individual discretion. As visual selective attention was not measured within Study 4, the authors cannot provide any further support to whether this was a contributing factor underlying the reliability of the data. Therefore, future research should utilise eye-tracking technology to measure visual selective attention to minimise the influence this may have on the data when assessing the reliability and validity of an esports perceptual-motor skill assessment. However, it is important to note that this type of methodology should be implemented in representative tasks that incorporate domain-specific measures, specific task goals and actions that accurately replicate the task demands of esports competition.

3. Cross-validation of statistical models in esports tournament performance

Study 5 demonstrated that the quantity of practice and in-game performance during practice explains a small proportion of the variance in tournament performance in Counter-Strike: Global Offensive. However, it is important to note that performance was only examined in one major esports tournament (PGL Major Krakow 2017). Given this reason, it limits the casual interpretation of the findings of Study 5 and makes it difficult to pinpoint to direct influences that practice has on tournament performance. Therefore, future research should consider cross-validating these findings in other tournaments to test the statistical model. For example, other events and tournaments include BLAST Premiers, Intel Extreme Masters, ESL Pro League, and Dreamhack Masters.

4. A micro-analysis of practice activities of professional esports players over a longitudinal period

Like Study 5, Study 6 highlighted that for relatively homogeneous populations performance metrics may not be directly associated with practice quantity. As such, it is likely that the quality of practice may be more useful to distinguish between performance levels in a homogeneous group of professional esports players. Additionally, Novak et al. (2020) suggested that more sophisticated models (i.e. Structural equation modelling and path analyses) are needed to truly capture how key performance indicators are associated with esports performances. Therefore, future research should also record the quality of in-game performance (kill/death ratio and score) at the smallest unit of analysis, rather than using average values over the duration of the study. Recording data at the smallest unit of analysis will improve the explanatory power within the statistical models. Furthermore, future research should expand upon the methodology of Study 6 and conduct a true longitudinal analysis of practice activities of esports players that spans several years.

5. Sex differences in esports players

While the sex of the participants recruited for all the of studies were mainly males, there were substantially less females recruited. Consequently, there was insufficient sample size that may not have sufficient statistical power to detect any meaningful effects when examining sex differences in esports players. Previously, females have performed significantly better than males on measures of verbal fluency and perceptual-motor speed (Halpern & LaMay, 2000; Weiss, Kemmler, Deisenhammer, Fleischhacker, & Delazer, 2003). Interestingly, Feng, Spence, and Pratt (2007) demonstrated that video game training can virtually eliminate sex differences in spatial attention. Therefore, examining sex differences in esports players and the confounding effect this may have on expertise requires future research.

Chapter 11:

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