The reliability and validity of mobalytics proving ground as a perceptual-motor skill assessment for esports

Article *in* International Journal of Sports Science & Coaching · March 2022

DOI: 10.1177/17479541221086793

The reliability and validity of Mobalytics Proving Ground as a perceptual-motor skill assessment for esports

Matthew A. Pluss[1], Andrew R Novak[1], Kyle J.M. Bennett[2], Derek Panchuk[3,4], Aaron J Coutts[1], and Job Fransen[1]

[1] Human Performance Research Centre, School of Sport, Exercise, and Rehabilitation, Faculty of Health, University of Technology Sydney, Moore Park, Australia.

[2] Faculty of Health, Southern Cross University, Coffs Harbour, Australia.

[3] Institute of Sport, Exercise and Active Living, Victoria University, Melbourne Australia.

[4] Movement Science, Australian Institute of Sport, Bruce, Australia.

Corresponding Author Contact Details

Kyle Bennett

Email: Kyle.Bennett@scu.edu.au

ORCID: https://orcid.org/0000-0002-2288-4770

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.

Funding

The author(s) received no financial support for the research, authorship, or publication

Published version

https://doi.org/10.1177/17479541221086793

The reliability and validity of Mobalytics Proving Ground as a perceptual-motor skill assessment for esports

Abstract

This study aimed to investigate the test-retest reliability and discriminant validity of the Mobalytics Proving Ground™ assessment for League of Legends. 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). Participants completed three separate trials (60 s each) online. 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 esports group and control group were moderate (ICC esports = 0.53 and ICC control = 0.72). The average 95% confidence intervals for the independent variables in the esports and control group were ICC = 0.30 – 0.75 and ICC = 0.55 – 0.86, respectively. A Friedman test revealed an effect size of 0.11 in the esports group and 0.07 in the control group. In terms of discriminant validity, there were significant differences for 17 variables when comparing the best scores of each group. Overall, the Mobalytics Proving Ground™ assessment used in the current study can, to some extent, distinguish esports players from controls.

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 receiving considerable attention from the sports science and psychology disciplines (Bányai, Griffiths, Király, & Demetrovics, 2019; Pedraza-Ramirez, Musculus, Raab, & Laborde, 2020; Pluss et al., 2019; Poulus, Coulter, Trotter, & Polman, 2021). In its simplest form, esports involve individuals or teams of players who compete in video game competitions through human-computer interactions (Pluss, et al., 2019). Although there are different 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 dynamic environment (Pluss et al., 2020). For example, in the multiplayer online battle area game League of Legends, players coordinate asymmetrical bimanual movements of the hands to control their mouse and keyboard, which are essential for performance. The mouse controls in-game character (i.e., champion) movements, standard attacks, and camera zoom, whereas the keyboard activates special attacks, spells that have unique effects (i.e., summon spells), and items. Players must also coordinate simultaneous actions of the mouse and keyboard (such as placing a ward, i.e., an item that allows a player to see more areas on the mini map).

Studies within other expertise domains such as sport provide an insight into the assessment of perceptual-motor skill (Bennett, Novak, Pluss, Coutts, & Fransen, 2020; Hadlow, Panchuk, Mann, Portus, & Abernethy, 2018; McGuckian, Cole, & Pepping, 2018; Tribolet, Bennett, Watsford, & Fransen, 2018). Typically, assessments involve players verbalising, writing, or executing the most appropriate response after viewing video footage of simulated match-based situations (O'Connor, Larkin, & Mark Williams, 2016; Vaeyens, Lenoir, Williams, Mazyn, & Philippaerts, 2007a; Vaeyens, Lenoir, Williams, & Philippaerts, 2007b; van Maarseveen, Oudejans, & Savelsbergh, 2015). Evidence from studies on perceptual-motor expertise in sport suggest that experts or players at higher competition levels can better perceive and respond to relevant environmental cues, revealing greater response accuracy and faster response times when compared with their non-expert or lower-level counterparts (Brams et al., 2019; Mann, Williams, Ward, & Janelle, 2007). Despite extensive research in sport, expertise differences in the perceptual-motor skills of esports players has received less attention (Pluss, et al., 2020), with many investigations primarily focusing on the association between video game experience and perceptual-motor abilities (Blacker and Curby, 2013; Chang, Liu, Chen, & Hsieh, 2017; Kokkinakis, Cowling, Drachen, & Wade, 2017) As such, future research should investigate esports players' perceptual-cognitive skills.

Anecdotally, perceptual-cognitive skills (e.g., mechanics [coordinating mouse and keyboard movements], background processing and map awareness) are integral to an esports player's skilful behaviour during competition. Players must perceive and interpret environmental information (e.g., the positioning of their virtual avatar, their teammates, and opposition) and execute specific actions (e.g., eliminate an opponent) appropriate to the imposed task demands (e.g., achieving an objective). Notably, just like in many sports, games like League of Legends require parallel processing, whereby attentional resources are divided among multiple simultaneous tasks. Further, competitive play involves frequent decision-making moments that are dynamically updated as a result of changes in the perceptual information embedded within the performance environment, which also aligns with the dynamic nature of decision making in sport. It is well known that in sport, designing task representative methodologies that encapsulate the perceptual-motor skills in a representative manner is complicated (Williams and Ericsson, 2005), with many designs not allowing participants to (re)produce the skilful behaviours observed in a real-world environment (Hadlow, et al., 2018).

While there is a common lack of task representativeness when assessing perceptual-cognitive skills in sport, the esports domain lends itself better to adhering to principles of representative task design. Foremost, in esports, the perception-action couplings of competition are more readily replicated in practice, because of the nature and adaptability of the virtual environments that form the performance context. The domain has already taken advantage of the malleable milieu in which esports are practiced by developing online testing applications (e.g., Mobalytics Proving Ground™). These online testing applications replicate some of the actions and decisions players make during competition and suggest they are capable of assessing core game-play perceptual-motor skills. However, while these assessments are popular, the infancy of the esports research domain means that their psychometric properties (i.e., validity and reliability) remain absent in research. As such, it is unknown whether these tools are appropriate to be used by esports coaches, players, and researchers. Therefore, the current study aimed to assess the test-retest reliability and discriminant validity of the Mobalytics Proving Ground™ online assessment using an expertise paradigm. It was hypothesised that there will be minimal differences between the results of successive measures carried out under the same conditions. Regarding discriminant validity, it was hypothesised that esports players would demonstrate superior skill performance compared with the control group.

Materials and Methods

Participants

Data were collected from 40 participants (age: 24.15 ± 3.68 y, sex: male = 31, female = 9). Participants were 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 participating in League of Legends (an average of 270.80 ± 169.23 games played since the start date of the current ranked season – 10th of January 2020). The competitive rank distribution of the players included within this study is as follows: Silver = 4 (top 69.2 – 40.6 % of players), Gold = 1 (top 34.3 – 13.6 % of players), Platinum = 6 (top 10.8 – 3.5 % of players), Diamond = 7 (top 2.5 – 0.26 % of players), Masters = 1 (top 0.085 – 0.051 % of players), and Challenger = 1 (top 0.015 % of players). The control group consisted of a convenience sample of healthy participants with minimal experience in League of Legends. 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 discriminant validity of the Mobalytics Providing Ground™ assessment in League of Legends. 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 accounts for individual differences in the responsiveness to a novel assessment. Subsequently, participants performed three separate trials of the assessment, whereby the aim was to achieve the highest score possible. A single trial of the assessment lasted 60 seconds. Participants completed the test with personal equipment (i.e., mouse and keyboard) and preferred settings (i.e., mouse sensitivity).

Mobalytics Proving Ground Assessment

Mobalytics Proving Ground (https://pg.mobalytics.gg/) is an online application that tests a player's mechanical ability, background processing, and map awareness through simulating different aspects of League of Legends game-play (Figure 1). The tool assesses mechanics (the ability to manipulate a mouse and keyboard in response to a perceptual stimulus) using randomly appearing targets. Clicking the bullseye rewards more points, whereas inaccurate clicking or failing to click a target before they disappear from the screen results in a loss of points. The tool assesses background processing using four bars that randomly deplete over several seconds. Participants receive points when they press the key (Q, W, E and R; default keys for the champion abilities in League of Legends) when the corresponding bar turns from red to green. Pressing the wrong key or missing the colour change leads to the bar becoming locked for five seconds, costing the participant an opportunity to score more points. The tool assesses map awareness using a mini map task where the goal is to dodge (move right = F and move left = D; default keys for the summoner spells in League of Legends) the obstacles that block the path. Contacting the obstacle results in the participant being stuck, limiting the opportunity to score more points. Table 1 details each component of mechanics, background processing, and map awareness that Mobalytics Proving Ground measures.

** Insert Figure 1 near here **

** Insert Table 1 near here **

Statistical analysis

All statistical analyses were conducted using R statistical software (R Development Core Team, New Zealand). 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 that 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 that each participant produced their best total score was used. 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.

Results

Table 2 displays the median ± interquartile range for individual trials. Table 3 reports the assessment of normal distributions, intraclass correlation coefficients, 95% confidence intervals, and ratings for all data. Table 4 contains the results of the Friedman tests, which includes the *p*-value, effect size, ratings, and the post hoc comparisons that compared each of the three trials for each group. Table 5 displays the differences between groups for the best score.

** Insert Table 2 near here **

Test-retest reliability

In terms of the data distribution, Seventeen out of 30 variables followed a normal distribution in the esports group, whereas seven out of 30 variables followed a normal distribution in the control group. The average ICC for all independent variables was 0.53 (range: 0.14 – 0.91) in the esports group and 0.72 (range: 0.15 – 0.94) and in the control. The average 95%

confidence intervals for the independent variables in the esports and control group was 0.30 – 0.75 (range: 0.00 – 0.96) and 0.55 – 0.86 (range: 0.04 – 0.97), respectively . Overall, test-retest reliability ranged from poor to good in both the esports and the control group. In terms of the Friedman test, nine independent variables reported a significance level of $p < 0.05$ in the esports group, whereas seven independent variables reported a significance level of $p < 0.05$ in the control group. The average effect size for the independent variables in the esports group was 0.11 and 0.07 in the control group. All effect sizes of the independent variables were small for both groups. When comparing results between trial one and trial two, significant differences ($p < 0.05$) were evident for background processing score (*n*) and background processing points lost (*n*) in the esports group. When comparing results between trial one and trial three, significant differences ($p < 0.05$) were evident for total score (*n*) and mechanics precision (%) in the esports group. 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*) were significantly different between trial one and three in the control group. When comparing results between trial two with trial three, a significant difference (p < 0.05) was evident for mechanics targets ignored (n) in the esports group only.

** Insert Table 3 and 4 near here **

Discriminant validity

There were 17 significant differences (adjusted significance level: $p < 0.0017$) observed when comparing the best scores of the esports group with the control group. Esports players displayed superior performances for all variables. The total score (*n*) and mechanics (*n*) summary score were significantly different between groups. The majority of the mechanics variables (59%) were significantly different between esports players and the control. All background processing variables were significantly different between groups. Only 20% of map awareness variables were significantly different between groups.

** Insert Table 5 near here **

Discussion

The current study investigated the test-retest reliability and discriminant validity of the Mobalytics Proving Ground™ assessment using an expertise paradigm. The Mobalytics

Proving Ground™ assessment is designed to measure perceptual-motor skills such as mechanical ability, background processing, and map awareness of a League of Legends player. Overall, most 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, using the best scores for each independent variable was deemed necessary to conduct group-wise comparisons. The esports group demonstrated superior skill performance compared with the control group using the total score and mechanics summary score. Background processing and map awareness summary scores did not discriminate between groups. When analysing the variables related to mechanics, background processing, and map awareness, most associated with mechanics and background processing significantly differed between groups. In contrast, map awareness variables did not distinguish esports players from controls. As a result, the assessment used in the current study can discriminate between an esports player and individuals with not competitive esports experience. However, it has limited applicability when aiming to quantify some of the performance characteristics of a League of Legends esports player.

The Mobalytics Proving Grounds™ assessment lacked stability across the different performance variables between multiple trials. One of the main issues potentially contributing to the lack of test-retest reliability is the absence of an explicit task goal within the assessment. The primary aim of the assessment is to achieve the highest score possible, which is determined by a somewhat unknown aggregation of performance across the three simultaneous tasks. This is in contrast to other perceptual-motor skill assessments in sport that have an explicit task goal such "make the correct decision quickly and accurately once the ball (is) played in the direction of the yellow player" (Vaeyens et al., 2009, p. 398) or "respond by passing the ball to the simulated free teammate" (McGuckian, Cole, Chalkley, Jordet, & Pepping, 2019, p. 36). As such, the uncertainty around how to achieve a high score likely resulted in participants adopting different strategies between trials. For example, a participant may have focused on scoring as many points as possible in the background processing task in one trial. Yet, the same participant may have focused on scoring as many points possible in the map awareness task for the subsequent trial. However, as selective visual attention was not measured within the current study, the authors cannot provide any further support for whether this was a contributing factor underlying the reliability of the data.

Therefore, future research should consider using eye-tracking technology to measure selective visual attention to minimise the influence this may have on the data when assessing the reliability of an esports perceptual-motor skill assessment.

Perceptual-motor abilities may underlie expertise in esports, yet their ability to distinguish between professional and recreational esports players is limited (Pluss, et al., 2020). It was recommended that future research include more domain-specific measures to fully capture the underlying characteristics of esports players. Although the current study incorporated more domain-specific measures (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 due to the reduced specificity in the perception-action coupling of specific aspects of the assessment (Araújo, Davids, & Passos, 2007; Hadlow, et al., 2018; Travassos et al., 2013). For example, with the background processing task, several bars 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 player's ability bar is located at the bottom of the screen. Further, players press the keys (e.g., Q, W, E and R) based on a cool-down timer, which is presented numerically (seconds) instead of changing colour. Therefore, these differences in perceptual-action coupling may explain the lack of association between some variables and esports expertise.

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 also 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, where the team has vision, and which objectives are coming next. However, players are not required to execute specific actions like those imposed in Mobalytics Proving Ground™ assessment (i.e., pressing the keyboard to move right or left to dodge the obstacle). Similarly, other studies that used assessments with non-specific actions presented limited evidence to support their employed methodological design's discriminant validity (Bennett, Novak, Pluss, Coutts, & Fransen, 2019; Keller, Raynor, Iredale, & Bruce, 2018; O'Connor, et al., 2016). Thus, it is crucial 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, the complete details of the control groups' video game experience were unknown, which might explain the higher inter-individual variance within their performance. Second, an additional testing session might have led to more stable performance by removing possible learning effect biases between trials Finally, given the limited applicability when aiming to quantify some of the performance characteristics of an esports player, the data obtained from the assessment may only indicate players' general perceptual-cognitive abilities rather than their specific perceptual-cognitive skills that are a characteristic of esports expertise.

Conclusion

The current study aimed to assess the test-retest reliability and discriminant validity and of an the Mobalytics Proving Ground™ assessment using an expert/non-expert paradigm. Overall, many variables had poor test-retest reliability. In terms of the main performance characteristics, the esports group demonstrated superior skill performance in total score and mechanics summary score compared with the control group. However, background processing and map awareness summary scores did not discriminate between groups. When analysing the variables related to each aspect of the performance characteristic, the majority of the variables associated with mechanics and background processing significantly differed between groups. At the same time, some of the 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 discriminate between an esports player and a control group. However, the assessment has limited applicability when quantifying the performance characteristics of an esports player. Therefore, when aiming to quantify performance in esports, it is important to use tasks with sufficient task representativeness (i.e., tasks that accurately replicate the perception-action couplings observed during competitive esports game play).

References

Abernethy, B., Baker, J., & Côté, J. (2005). Transfer of pattern recall skills may contribute to the development of sport expertise. Applied Cognitive Psychology: The Official Journal of the Society for Applied Research in Memory and Cognition, 19(6), 705-718.

Bányai, F., Griffiths, M. D., Király, O., & Demetrovics, Z. (2019). The psychology of esports: A systematic literature review. Journal of gambling studies, 35(2), 351-365.

Abernethy, B., Baker, J., & Côté, J. (2005). Transfer of pattern recall skills may contribute to the development of sport expertise. *Applied Cognitive Psychology, 19*(6), pp. 705-718.

Araújo, D., Davids, K., & Passos, P. (2007). Ecological validity, representative design, and correspondence between experimnental task constraints and behavioural setting: Comment on Rogers, Kadar, and Costall (2005). *Ecological psychology, 19*(1), pp. 69-78.

Bányai, F., Griffiths, M. D., Király, O., & Demetrovics, Z. (2019). The psychology of esports: A systematic literature review. *Journal of gambling studies, 35*(2), pp. 351-365.

Bennett, K. J., Novak, A. R., Pluss, M. A., Coutts, A. J., & Fransen, J. (2019). Assessing the validity of a video-based decision-making assessment for talent identification in youth soccer. *Journal of Science and Medicine in Sport, 22*(6), pp. 729-734.

Bennett, K. J., Novak, A. R., Pluss, M. A., Coutts, A. J., & Fransen, J. (2020). A multifactorial comparison of Australian youth soccer players' performance characteristics. *International Journal of Sports Science & Coaching, 15*(1), pp. 17-25.

Blacker, K. J., & Curby, K. M. (2013). Enhanced visual short-term memory in action video game players. *Attention, Perception, & Psychophysics, 75*(6), pp. 1128-1136.

Brams, S., Ziv, G., Levin, O., Spitz, J., Wagemans, J., Williams, A. M., & Helsen, W. F. (2019). The relationship between gaze behavior, expertise, and performance: A systematic review. *Psychological bulletin, 145*(10), p 980.

Chang, Y.-H., Liu, D.-C., Chen, Y.-Q., & Hsieh, S. (2017). The relationship between online game experience and multitasking ability in a vitual environment. *Applied Cognitive Psychology, 31*(6), pp. 653-661. doi:https://doi.org/10.1002/acp.3368

Garmer, M., Lemon, J., Fellows, I., & Singh, S. (2014). Various coefficients of interrater reliability and agreement.

Hadlow, S. M., Panchuk, D., Mann, D. L., Portus, M. R., & Abernethy, B. (2018). Modified perceptual training in sport: a new classification framework. *Journal of Science and Medicine in Sport, 21*(9), pp. 950-958.

Kassambara, A. (2019). rstatix: Pipe-Friendly Framework for Basic Statistical Tests.

Keller, B. S., Raynor, A. J., Iredale, F., & Bruce, L. (2018). Tactical skill in Australian youth soccer: Does it discriminate age-match skill levels? *International Journal of Sports Science & Coaching, 13*(6), pp. 1057-1063.

Kokkinakis, A. V., Cowling, P. I., Drachen, A., & Wade, A. R. (2017). Exploring the relationship between video game expertise and fluid intelligence. *PLOS one, 12*(11), p e0186621.

Koo, T. K., & Li, M. Y. (2016). A guideline of selecting and reporting intraclass correlation coefficients for reliability research. *Journal of chiropractic medicine, 15*(2), pp. 155-163.

Korkmaz, S., Goksuluk, D., & Zararsiz, G. (2014). MVN: An R package for assessing multivariate normality. *The R Journal, 6*(2), pp. 151-162.

Kowal, M., Toth, A. J., Exton, C., & Campbell, M. J. (2018). Different cognitive abilities displayed by action video gamers and non-gamers. *Computers in Human Behavior, 88*, pp. 255-262.

Mann, D. T., Williams, A. M., Ward, P., & Janelle, C. M. (2007). Perceptual-cognitive expertise in sport: A meta-analysis. *Journal of Sport and Exercise Psychology, 29*(4), pp. 457-478.

McGuckian, T. B., Cole, M. H., Chalkley, D., Jordet, G., & Pepping, G.-J. (2019). Visual exploration when surrounded by affordances: Frequency of head movements is predictive of response speed. *Ecological psychology, 31*(1), pp. 30-48.

McGuckian, T. B., Cole, M. H., & Pepping, G.-J. (2018). A systematic review of the technology-based assessment of visual perception and exploration behaviour in association football. *Journal of sports sciences, 36*(8), pp. 861-880.

O'Connor, D., Larkin, P., & Mark Williams, A. (2016). Talent identification and selection in elite youth football: An Australian context. *European journal of sport science, 16*(7), pp. 837-844.

Pedraza-Ramirez, I., Musculus, L., Raab, M., & Laborde, S. (2020). Setting the scientific stage for esports psychology: A systematic review. *International Review of Sport and Exercise Psychology*, pp. 1-34.

Pluss, M. A., Bennett, K. J. M., Novak, A. R., Panchuk, D., Coutts, A. J., & Fransen, J. (2019). Esports: The Chess of the 21st Century. [Perspective]. *Frontiers in psychology, 10*(156)doi:10.3389/fpsyg.2019.00156 Retrieved from https://www.frontiersin.org/article/10.3389/fpsyg.2019.00156

Pluss, M. A., Novak, A. R., Bennett, K. J., Panchuk, D., Coutts, A. J., & Fransen, J. (2020). Perceptual-motor Abilities Underlying Expertise in Esports. *Journal of Expertise/March, 3*(2)

Poulus, D. R., Coulter, T., J, Trotter, M. G., & Polman, R. (2021). A qualitative analysis of the perceived determinants of success in elite esports athletes. *Journal of Sports Sciences*, pp. 1-12. doi:https://doi.org/10.1080/02640414.2021.2015916

Travassos, B., Araújo, D., Davids, K., O'Hara, K., Leitão, J., & Cortinhas, A. (2013). Expertise effects on decision-making in sport are constrained by requisite response behaviours - A meta-analysis. *Psychology of Sport and Exercise, 14*(2), pp. 211-219. doi:10.1016/j.psychsport.2012.11.002

Tribolet, R., Bennett, K. J., Watsford, M. L., & Fransen, J. (2018). A multidimensional approach to talent identification and selection in high-level youth Australian football players. *Journal of sports sciences, 36*(22), pp. 2537-2543.

Vaeyens, R., Lenoir, M., Williams, A. M., Mazyn, L., & Philippaerts, R. M. (2007a). The effects of task constraints on visual search behavior and decision-making skill in youth soccer players. *Journal of Sport and Exercise Psychology, 29*(2), pp. 147-169.

Vaeyens, R., Lenoir, M., Williams, A. M., & Philippaerts, R. M. (2007b). Mechanisms underpinning successful decision making in skilled youth soccer players: An analysis of visual search behaviors. *Journal of Motor Behavior, 39*(5), pp. 395-408.

van Maarseveen, M. J., Oudejans, R. R., & Savelsbergh, G. J. (2015). Pattern recall skills of talented soccer players: Two new methods applied. *Human Movement Science, 41*, pp. 59-75.

Williams, A. M., & Ericsson, K. A. (2005). Perceptual-cognitive expertise in sport: Some considerations when applying the expert performance approach. *Human Movement Science, 24*(3), pp. 283-307. doi:10.1016/j.humov.2005.06.002

Tables

Table 1. The variables for each of the 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)		

Table 2. Median and interquartile range for each trial.

	Trial 1		Trial 2		Trial 3	
Independent variables	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)
Mechanics (n)	47.5 (21.5)	74.5 (3.5)	48 (16.5)	76.5 (7.5)	49 (12.5)	77 (7.5)
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)
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)
Mechanics						
Target hits (n)	62.5 (43.8)	113 (6.5)	63 (35.2)	114 (5.2)	66 (39.2)	115 (3)
Accuracy (%)	90 (10)	90 (2.5)	85 (10)	90 (10)	90 (10)	90 (10)
Precision (%)	34.5 (26.5)	69 (6.2)	33.5 (23)	71.5 (8.5)	36.5 (19.2)	71 (10.2)
Targets ignored (n)	48.5 (42.5)	1 (4.2)	49 (33.5)	2 (4.2)	46 (42)	1 (2.2)
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)
Centre hits (n)	30.5 (13.8)	47.5 (9)	32 (12.5)	51.5 (12.8)	29 (11.8)	51.5 (18.2)
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)
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)
Middle hits (n)	29 (22.2)	48 (6.8)	26 (19.5)	46.5 (7.8)	32.5 (26.8)	47 (12.2)
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)
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)
Border hits (n)	8.5 (10.8)	15.5 (7)	8 (13.2)	13 (8.2)	8.5 (9.2)	12 (7)
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)
Points from border hits (n)	8.5 (10.8)	15.5 (7)	8 (13.2)	13 (8.2)	8.5 (9.2)	12 (7)
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)
Actions per minute (n)	121 (40.2)	167.5 (18.2)	114.5 (49.5)	168 (12.2)	115.5 (46)	165 (13)
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)
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)
Points lost (n)	384.7 (89.5)	322 (94.6)	401.2 (126)	322 (94.6)	385.7 (98.2)	292.4 (107.5)
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)
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)
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)
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)
Points lost (n)	255.7 (203.1)	122.5 (75.2)	293 (200.2)	82 (106.7)	205 (127.9)	76.8 (109.5)
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)
Obstacles avoided (n)	0 (0)	0 (1)	0 (0)	0 (1.2)	0 (1)	0 (2.2)

Note: n = number, % = percent, s = seconds.

Table 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 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 ($p < 0.05$).*

Table 5. Aggregated values for the trials where each player achieved their best scores per group.

Independent variables	Control	Esports
Total score (n)	1016.9 (251.7)	1424.2 (148.3)*
Mechanics (n)	49 (18.5)	79 (8)*
Background processing (n)	15.9 (14.8)	24.8 (11.5)
Map awareness (n)	61 (24.7)	82.8 (19.8)
Mechanics		
Target hits (n)	68 (39.2)	114 (5)*
Accuracy (%)	90 (10)	100 (10)*
Precision (%)	36.5 (23.2)	73.5 (8.2)*
Targets ignored (n)	47 (40.5)	1 (4.2)*
Total points lost (n)	409 (180.8)	151 (54)*
Centre hits (n)	39.5 (18.5)	50 (10.5)*
Centre hits of all hits (n)	39.5 (18.5)	50 (10.5)
Points from centre hits (n)	157.5 (72.5)	272 (65)*
Middle hits (n)	34 (23.5)	44 (9.5)
Middle hits of all hits (n)	43 (9.5)	39 (7.2)
Points from middle hits (n)	102 (70.5)	132 (28.5)
Border hits (n)	9.5 (9.5)	10 (7.5)
Border hits of all hits (n)	12.5 (9)	8.5 (6.5)
Points from border hits (n)	9.5 (9.5)	10 (7.5)
Average click delays (s)	1.4 (0.6)	0.8 (0.3)*
Actions per minute (n)	119.5 (46.8)	165 (17.5)*
Centre points lost (n)	324.5 (109)	147 (47)*
Background processing		
Score (n)	146.2 (109)	208.3 (102)*
Points lost (n)	353.9 (109)	291.6 (102)*
Total number of block bars (n)	16 (10)	9 (5.5)*
Time locked out (s)	62 (39)	30.5 (18.1)*
Map awareness		
Score (n)	305.2 (122.9)	414.4 (99)
Time stuck (s)	5.7 (5.3)	2.5 (2.8)
Points lost (n)	194.8 (123.2)	85.7 (99)
Average time per obstacle (s)	0.6 (0.4)	0.3 (0.2)*
Obstacles avoided (n)	0 (1)	0.5 (3)

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

Figures

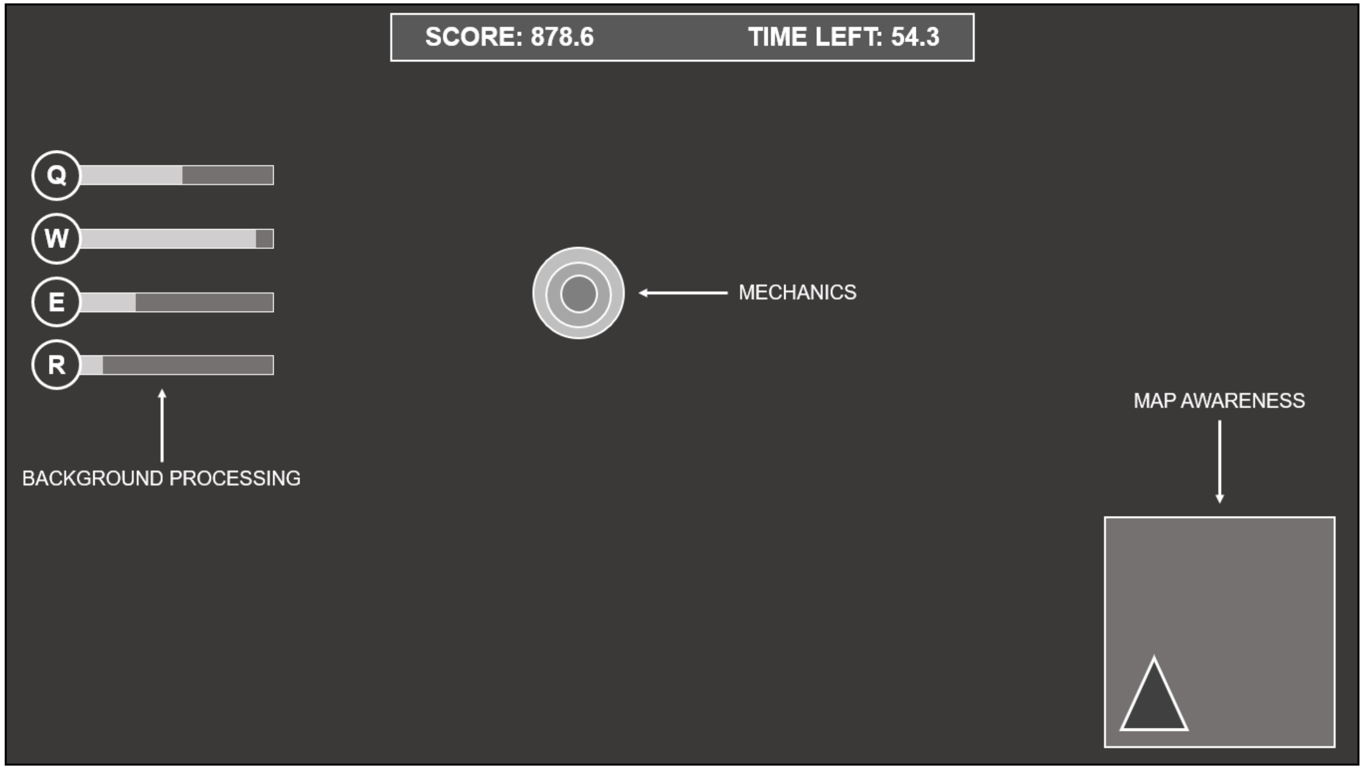
SCORE: 878.6
TIME LEFT: 54.3
Q
W
E
R
MECHANICS
BACKGROUND PROCESSING
MAP AWARENESS

Figure Captions

Figure 1. A visual representation of the online esports perceptual-motor skill assessment.