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# The relationship between the quantity of practice and in-game performance during practice with tournament performance in esports: An eight-week 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 was 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 a significant average kill/death ratio + average score main effect on tournament performance was identified ($p < 0.001$, $R^2 = 0.30$). 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%, $t = 3.89$, $p \leq 0.001$). 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 explained a small proportion of the variance in tournament performance. More specifically, the variables that were most associated with better tournament performance were 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.*

## 1. 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, Bennett, Pluss, & Fransen, 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, Toth, Exton, & Campbell, 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, Krampe, & Tesch-Römer,

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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, Côté, & Abernethy, 2003; Charness, Tuffiash, Krampe, Reingold, & Vasyukova, 2005; Côté, Baker, & Abernethy, 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, Hodges, Starkes, & Williams, 2007). In many domains, the attainment of expertise can be influenced by the time engaged in practice (Baker, 2003; Baker, Cobley, & Fraser-Thomas, 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 must be deliberate and purposeful to attain expertise (Charness et al., 2005; Ericsson et al., 1993). 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).

Many studies typically observe practice over extended periods of time (e.g., months to years), practice can also provide acute (e.g., days to weeks) performance outcomes and performance improvements (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 (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 of the relationship between practice and performance. Therefore, the present study employed 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 proportion of the variance in tournament performance (Macnamara, Moreau, & Hambrick, 2016; Young, 1998).

## 2. Methods

### *2.1. Participants*

Data was 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.

### *2.2. 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. 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 typically involves practice focused on developing individual skills whilst time spent in competition is practice in a competitive team-based environment. 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) with the ability to purchase any primary and secondary weapons with no regards to the money economy, which is not evident in a competition setting. Each match lasts 10 minutes and the player with the highest points wins the round. Time spent in competition involves two teams (Terrorist and Counter-Terrorist) 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. Each round is one minute and 45 seconds long, however, if the Terrorists manage 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). Data was 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 25th and 75th percentiles ± 1.5 × IQR (Hoaglin & Iglewicz, 1987; Hoaglin, Iglewicz, & Tukey, 1986). After discarding outliers, the current study used a total of 284 observations from 43 participant's (~6.6 observations per participant). Table 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: $p < 0.001$).

### 2.3. Statistical analysis

Prior to analysis, the distribution of the dependent variable was visually inspected using 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 (Grewal, Cote, & Baumgartner, 2004). 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

Table 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 |

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).

## 3. Results

Figure 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 2 displays the Akaike Information Criterion (AIC), explained variance (marginal R2), conditional explained variance (conditional R2), 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 ($p \leq 0.001$). At six weeks out from competition, the linear mixed effects model identified a significant kill/death ratio main effect on tournament performance ($p \leq 0.001$). At five weeks out from competition, the linear mixed effects model identified a significant time spent in-game main effect on tournament performance ($p \leq 0.001$). At four weeks out from competition, the linear mixed effects model identified a significant kill/death ratio main effect on tournament performance ($p \leq 0.001$). 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 ($p \leq 0.001$). At one week out from competition, the linear mixed effects model identified a significant kill/death ratio main effect on tournament performance ($p \leq 0.001$). In the average model, the linear mixed effects model identified a significant average kill/death ratio + average score main effect on tournament performance ($p \leq 0.001$). Table 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. Also, Table 3 displays the best fitting models with the 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, $p \leq 0.001$). 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 2: The effects of accumulated values and weekly values on tournament performance

| | Best fitting weekly models explaining tournament score | | | | |
|---|---|---|---|---|---|
| Models | 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 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.

## 4. 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 (number 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, practice which is deliberate and purposeful is likely 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 types 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

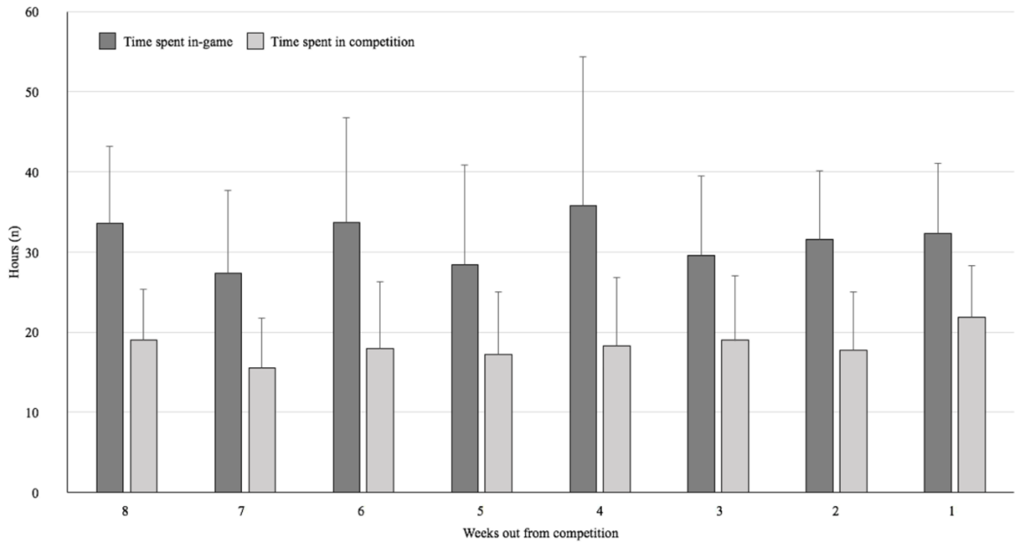


Figure 1: The average amount of time spent in-game and the average amount of time spent in competition each week out of competition (presented as mean ± SD)

explain the acute effects that practice has on tournament performance (Côté, Baker, & Abernethy, 2003). However, future research is needed to support this hypothesis as the specific goals and motives of 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, the 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 of 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 the 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 slow and calls out opponents' positions, which often results in a higher kill/death ratio.

### *4.1. Limitations and future directions*

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 the 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 (Eccles & Feltovich, 2008). 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 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. 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.

## 5. 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 practice which is deliberate and purposeful is likely 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.

## Conflict of Interest

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.

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