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The Practice Behaviors of Expert League of Legends Players: An Exploratory Study

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ABSTRACT
This exploratory study addressed a knowledge gap in the practice behaviours of ranked League of Legends players. We sourced data on a random sample of players ($n = 913$) from four competitive tiers and eight servers. We derived practice behaviour metrics from their last 100 matches. Challenger players had more matches per day, less variability in total hours, went fewer days without a match, and had the most matches in three- and seven-day blocks than other tiers. Servers with larger player pools tended to have more daily practice than comparatively smaller servers. We devised several hypotheses: (1) the volume of solo/duo ranked practice is associated with expertise, (2) more effective stress-coping strategies explain the lower variability in daily practice hours between tiers, (3) there is an interrelationship between player pool size, competitiveness, and practice behaviors, and (4) there are distinct patterns of practice associated with sustained participation or prolonged disengagement.

KEYWORDS
Esports; video gaming; ranked; skilled

1. Introduction

Esports, the playing of competitive video games (Pedraza-Ramirez et al., 2020), has attracted increased scientific attention in recent years (Poulus et al., 2024; Reitman et al., 2020), possibly due to its immense popularity among young people and increased professionalization in a competitive sense. Esports has moved far beyond small gatherings in niche gaming communities, evolving into a global phenomenon, with numerous major international tournaments, such as the Esports World Cup. The competitive domain has developed so far that an Olympic Esports Games is possible in the foreseeable future (International Olympics Committee, 2024). While esports was largely a self-directed recreational pursuit in the past, players now have facilities, schedules, and support comparable to traditional athletes. In many instances, esports players will engage in hours of team and individual practice, planning and video review sessions, team-building activities, and personal development (Pedraza-Ramirez et al., 2020; Poulus et al., 2022a). They also have performance facilities for their training and support staff working with them, including coaches, analysts, sports psychologists, and sometimes strength and conditioning specialists (Zalamea, 2022). Consequently, innovation in performance optimization, talent identification, and expertise development is now at the forefront of professional organizations looking to succeed at domestic and international levels.

Among the esports titles, League of Legends (Riot Games, California, USA) stands out as one of the most competitive at domestic and international levels, featuring numerous tournament seasons in each domestic region, culminating in major international tournaments attended by the highest performing teams in each region – Mid-Season Invitational and World Championships. Established regions

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(i.e., major regions), such as Korea and China, have historically dominated these international tournaments, winning all but one of the titles at the Mid-Season Invitational and 85% of the World Championships (Stewart, 2024). In contrast, teams from emerging regions (i.e., minor regions), which include areas with less developed esports infrastructure and/or smaller populations like Oceania, often struggle to qualify, are allocated fewer positions, and rarely progress far in these competitions. For example, Oceania's League of Legends Professional competition has been replaced or refreshed twice. In 2020, Riot Games announced that the Oceanic Pro League (2015–2022) would be dissolved due to operational costs and replaced by the League of Legends Circuit Oceania. In 2024, the same competition folded due to similar resourcing issues (Taifalos, 2024). A likely contributor to this disparity is the size and depth of the player participation pool. This pool extends beyond the professional environment into publicly accessible ranked match play, where any player with access to the game can compete to climb skill-based ladders and achieve higher ranks via winning matches. In this environment, millions of players practice to become more skilled, serving as the primary talent pool for professional organizations to recruit future players.

Unlike most traditional sports, where much of a player's development occurs in academy systems (Burgess & Naughton, 2010), many esports players learn in a primarily unstructured and self-regulated environment (Bubna et al., 2023). In other words, the players themselves are responsible for devising strategies for improvement, albeit some do seek mentorship from other skilled players or amateur coaches. While semiprofessional academy programs exist in some esports regions, these typically cater to relatively few players when compared with traditional sports programs that may include structured training programs and coaching for hundreds of athletes. For this reason, the esports learning environment offers a novel context in which to study expertise development and performance. While research has begun to explore this area in professional and semiprofessional players (Pluss et al., 2021, 2022), these studies have concentrated on a single video game, and it is unknown if these trends extend beyond the game context. As such, a substantial evidence gap remains, particularly concerning the practice behaviors that contribute to expertise across ranked players that sit outside of professional and semiprofessional tiers. As a result of this evidence gap, there is limited understanding of how skill develops in the absence of formalized training systems.

Empirical evidence from traditional sports literature suggests that there might be an association between the amount and type of practice and the development of expertise (Baker & Young, 2014; Williams & Ford, 2008). Some investigations suggest that the amount of domain-specific practice contributes to expertise development (Baker et al., 2003; Ward et al., 2007), while others note the value of engaging in play-based activities or unstructured training (Ford et al., 2009). It is likely that there are several possible avenues to expert performance, with various types of practices contributing in different ways (Côté et al., 2007). Despite such studies being more abundant in traditional sports and offering insights into the volume and type of practice activities that might lead to world-class performance (Rees et al., 2016), many use retrospective recall techniques. These methods rely on athletes documenting or discussing their developmental histories through questionnaires or interviews (e.g., Ford et al., 2009; Güllich, 2014). While adopting a similar study design in esports might address the evidence gap, methodological limitations, such as estimation errors or misremembering of milestones, impact the ability of researchers to collect accurate data with which to draw inferences and offer practical implications (Howard, 2011).

An alternative approach researchers can use in esports is accessing and analyzing data repositories available through the game developer (Deng et al., 2024). For example, Riot Games – the developer of League of Legends – provides an extensive application programming interface (API) containing practice (e.g., frequency and duration of matches) and performance (e.g., kills, deaths, and assists) data for all players engaged in ranked matchmaking play. Utilizing such data offers the opportunity to improve reporting accuracy, mitigating recall biases and providing real-time insights into player development patterns. Therefore, the current study addresses the evidence and methodology gap by analyzing publicly available match data from players who are relative experts across established and emerging regions. It adopts an exploratory design to generate preliminary insights that can inform future confirmatory research and practice applications in talent identification and development within the esports industry. Consequently, we opted not to conduct explicit hypothesis testing.

2. Methods

2.1. Context

League of Legends is a team-based multiplayer online battle arena video game. It involves teams of five players controlling a champion (i.e., assassin, fighter, mage, marksman, support, tank) with unique abilities. The player uses this champion to defeat minions and enemy players, rewarding them with gold and experience, which allows their champion to get progressively stronger by leveling up. The player can use the gold to buy items, boosting the champion's power so they can do more damage. Throughout the game, the team can defeat neutral objectives, providing them with a buff and temporarily increasing their power. The game ends when the team destroys the opposition's base. See Novak et al. (2019, 2020) for additional details about League of Legends matchplay.

League of Legends has an in-built matchmaking system based on relative skill levels (akin to the Elo rating system used in chess and sports), with ten tiers of competition, progressing from least to most skillful (i.e., Iron, Bronze, Silver, Gold, Platinum, Emerald, Diamond, Master, Grandmaster, and Challenger). These tiers have four sub-divisions, except for Master, Grandmaster, and Challenger, which only have one. Players progress up the competitive ladder by winning matches, which earns them League Points. Once they have achieved 100 League Points within a division, they move to the subsequent division. Once they reach the top division within a tier (e.g., Gold I), they advance to the lowest level of the next tier (i.e., Platinum IV). The matchmaking system has several game modes, with the ranked option relevant to the current study. We specifically focused on the Solo/Duo queue as it reflected independent practice. In contrast, Flex Queue requires a party of three or more players and may be more indicative of team-based practice.

2.2. Sample characteristics

We designed the sample characteristics for this exploratory study using our domain knowledge (all authors have League of Legends playing experience and have worked with professional teams) and pragmatic decisions (the API restricts requests to 100 every two minutes and subsequent data processing limitations). The target sample for the present study was 30 players from each of four tiers across eight servers (i.e., $30 \times 4 \times 8 = 960$ total players. Specifically, the sample was League of Legends players who had achieved the Challenger, Grandmaster, Master, or Emerald I tiers of the matchmaking ladder. It is difficult to provide the exact distribution of these players as thousands of games are being played at any one time, and the distributions shift dynamically; however, Challenger is in approximately the top 0.025% of players in a region, Grandmaster is 0.025–0.075%, and Master is 0.075–0.85% (League of Graphs, 2024). Comparatively, Emerald I players are approximately the top 6–7%, representing skilled players with less relative expertise than the top three tiers.

Given the API rate limits and data processing times, we sampled two servers from each of the four regions as defined by the Riot Games API documentation (Americas, Europe, Asia, and Southeast Asia). The sampling approach aimed to approximate a representative sample of high-tier players across diverse regions and server sizes. Therefore, within each region, we included one server with a relatively high number of total players across all tiers and one with a relatively low number of total players across all tiers. The servers in the relatively large category were North America, Korea, Europe West, and Vietnam. The servers in the relatively small sample were Brazil, Japan, Russia, and Singapore, Malaysia, and Indonesia (a combined server). We implemented a randomized sampling approach via R statistical software from each server to select 30 random players ranked in each tier from a list of queried players returned by the API. However, not all servers had 30 players within each tier when the data were collected, possibly due to the recent beginning of a new League of Legends season, which resets the player rankings. We included all available players from the tier when fewer than 30 were present; therefore, the sample represents a disproportionate stratified random sampling approach as the small cohorts of highest performing players are of interest when studying expertise.

The Southern Cross University Human Research Ethics Committee approved the current study (Approval number = 2024/043).

2.3. Data processing procedures

We queried data from the Riot Games API using an approved development API key. We used R statistical programming to access the last 100 completed matches of each player within the sample. Although the API stores up to 1000 games of data per player, it was not feasible to query such a high volume of data for 913 players (913,000 total queries) at a rate limit of 100 queries per two minutes. Parallel processing was implemented to improve processing time (concurrent queries running per server), although at most, this can improve processing by four times, given that API limits are at the region level. In some cases, matches were unavailable for some players, so players were only included in the final analysis if their most recent 100 completed matches were returned by the API. See Table 1 for the final count of players per tier and server for which the most recent 100 completed matches were retrieved. We did not conduct a formal power analysis due to the exploratory nature of the study. Instead, we focused on gathering sufficient data to identify preliminary patterns and generate hypotheses for future research.

The variables of interest for our analysis included the date and time of each match, as well as the match duration. From these contextual factors, we calculated additional, such as the number of games per day, number of days in which at least one game was played, number of days played in a row, number of days without play in a row, most games played in one day, most games played in a three-day period, and the ratio of days played vs. not played.

2.4. Statistical analysis

We conducted all data extraction and preliminary processing using R (v4.1.2, R Core Team, Vienna, Austria) in R Studio (v2021.09.2, R Studio Team, Boston, MA). Data for all players were combined into a single file, which we imported into Tableau and Excel to generate summary statistics and data visualizations, while we used R for further modeling.

2.4.1. Exploring differences in practice behavior between servers and tiers

To explore differences in practice behavior between groups (i.e., servers and tiers, including interaction effects), we used the continuous variable *hours per day* as the dependent variable. We identified outliers using a labeling rule of 1.5 x interquartile range. We labeled 32 observations as outliers, although we retained them in further analysis as they appear to be realistic values, and removal had little effect on model outputs. We plotted the *hours per day* variable for each level of grouping and inspected the QQ plots. Some groups had a non-normal distribution, and the residuals of fitted models displayed deviation from homoscedasticity, so we tested rank and log transformations in two-way ANOVA models via the stats package in R (v3.6.2, R Core Team). Log transformation produced the best distribution of residuals as viewed in the residual distribution plot, QQ plot and a Shapiro-Wilk test of residuals, so we retained this as the final model for this exploratory analysis. Following this, pairwise Wilcoxon tests were used to compare individual tiers and servers. An alpha level of 0.05 was set to identify potential differences between groups, and we applied a Bonferroni correction to multiple comparisons.

2.4.2. Identifying different types of practice behaviors

To identify different practice behaviors, we conducted a hierarchical cluster analysis on four metrics, which we found to be not multicollinear ($r < 0.80$), including (1) *the ratio of days with practice to days without practice;* (2) *the most number of games played in a one-day period;* (3) *the most number of games*

Table 1. The sample size per server and tier.

	Relatively small				Relatively large				
Tier	BR1	JP1	RU	SG2	NA	KR	EUW1	VN2	Total
Challenger	30	30	27	20	30	30	30	30	227
Grandmaster	30	30	25	20	30	30	30	30	225
Master	30	30	30	25	30	30	30	27	232
Emerald I	30	30	30	19	30	30	30	30	229
Total	120	120	112	84	120	120	120	117	913

Note: Brazil, NA1 = North America, JP1 = Japan, KR = Republic of Korea, EUW1 = Europe West, RU = Russia, SG2 = Singapore, Malaysia, and Indonesia, VN2 = Vietnam.

played across a three-day period; and (4) *the most days without practice in a row*. We scaled all variables to a range between 0 and 1 before clustering. We conducted the analysis via the stats package in R (v3.6.2, R Core Team) using the Euclidean distance and Ward's minimum distance to minimize increases in the within-cluster variance. We used visual inspection of the clustering tree and the distribution of variables within each group to identify practice behavior types that could be easily interpreted.

3. Results

3.1. Descriptive data

3.1.1. Number and duration of matches per day

Challenger players (highest tier) across all servers (except Europe West) tended to have the greatest number of ranked solo/due queue matches per day, whereas Emerald I players (lowest tier) had the least (excluding Japan and Vietnam). The average number of matches per tier when pooling these data was 4.7 ± 2.1, 4.3 ± 2.4, 3.4 ± 2.2, and 3.1 ± 1.84 for Challenger, Grandmaster, Master, and Emerald tiers, respectively. The relatively large servers had an average of 0.6 more matches per day than the relatively small ones (4.1 ± 2.3 vs. 3.5 ± 2.1). The Korean server had the highest combined average for the number of matches per day of any other region (Figure 1(a)).

When removing the days when players had no matches, the average number of ranked solo/due queue matches per day increased by 2.0 ± 1.2. The average number of daily matches was as high as 7.6 among Korean Challenger players (Table 2).

The average ranked solo/duo queue match was at least 20 min, irrespective of the player's tier or server (Figure 1(b)). Average match durations were similar across tiers, with slightly shorter durations in the Challenger tier (25.4 ± 1.2 min vs. 25.5 ± 1.2, 26.1 ± 1.2, 27.5 ± 1.1 mins, for Grandmaster, Master, and Emerald tiers, respectively). The average match durations were somewhat longer in relatively small (26.6 ± 1.2 mins) than in relatively large (25.7 ± 1.5 mins) servers.

3.1.2. Total practice hours

Challenger players had the highest volume of practice in six out of the eight servers (Figure 2(a)). The average total practice hours for Challenger, Grandmaster, Master, and Emerald I players were 1.98 ± 0.88, 1.83 ± 1.00, 1.48 ± 0.93, and 1.40 ± 0.83 h, respectively. The average total practice hours per day was slightly longer in relatively large than small servers (1.77 ± 0.95 vs. $1.56 \pm$ Y 0.92 h).

There was substantial variability within ranked practice hours per day (Figure 2(b)). Generally, Challenger players had the lowest variability in ranked practice, with a pooled coefficient of variation of 44.6%. This was lower than Grandmaster (54.6%), Master (62.9%), and Emerald I (59.3%). The variability was comparable between relatively large (54.1%) and small (58.8%) servers. The lowest variability existed in the Korean Challenger players group.

3.1.3. Practice behaviors

Most players within the sample spent approximately two weeks playing at least one ranked solo/due queue match per day (Table 3). In some instances, the number of days with at least one game reached 25 in North American players. The greatest number of days without a match was comparatively lower, with an average value ranging between 3.1 and 6.1 across servers and tiers. The average of most days without a match increased as tier decreased (Challenger $= 4.0 \pm 2.0$, Grandmaster $= 4.4 \pm 2.1$, Master $= 5.2 \pm 2.0$, Emerald I $= 5.3 \pm 1.9$). The average of most days without a match was similar between relatively large and small servers (4.5 ± 2.0 vs. 4.9 ± 2.1).

When analyzing the matches across three- and seven-day blocks, the total number of matches reached 34.9 (Japan) and 58.4 (Singapore, Malaysia, and Indonesia), respectively. Challenger players tended to have the most matches in a three-day (32.1 ± 9.7) and seven-day (53.7 ± 15.1) block, and Emerald I players had the least (25.4 ± 8.7 and 42.0 ± 14.2, respectively). Three-day and seven-day blocks were slightly higher in relatively large compared with relatively small servers (29.2 ± 9.8 and 48.5 ± 15.8 vs. 28.4 ± 9.9 and 46.8 ± 16.9, respectively).

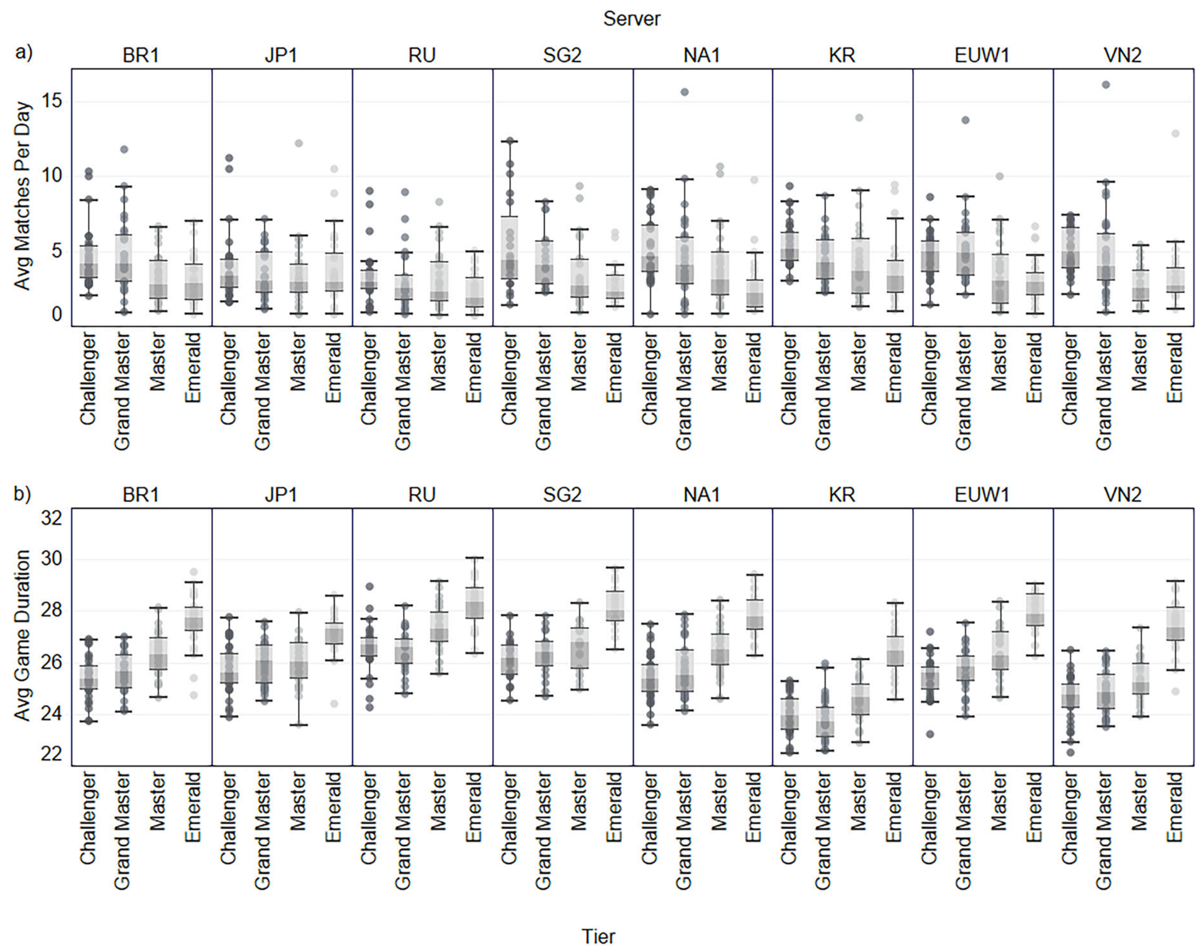

Figure 1. The (a) average number and (b) duration of matches per day according to server and tier. *Note:* BR1 = Brazil, JP1 = Japan, RU = Russia, SG2 = Singapore, Malaysia, and Indonesia, NA1 = North America, KR = Republic of Korea, EUW1 = Europe West, VN2 = Vietnam.

Table 2. The mean number of matches per day (removing days without play) based on server and tier.

	Tier			
Servers	Challenger	Grandmaster	Master	Emerald 1
BR1	5.9 ± 1.9	6.3 ± 2.3	5.1 ± 1.2	4.9 ± 1.9
JP1	6.7 ± 2.4	5.8 ± 1.8	5.5 ± 2.0	5.6 ± 2.2
RU	5.4 ± 1.7	4.9 ± 1.8	5.0 ± 1.9	4.9 ± 1.8
SG2	7.0 ± 2.7	6.2 ± 2.1	5.4 ± 2.2	5.0 ± 1.9
NA1	7.0 ± 2.4	6.5 ± 2.8	5.5 ± 2.6	4.3 ± 1.4
KR	7.6 ± 2.0	6.7 ± 2.5	6.7 ± 2.7	6.3 ± 2.3
EUW1	5.9 ± 1.8	6.9 ± 2.2	5.4 ± 2.2	4.9 ± 1.3
VN2	7.0 ± 1.9	6.9 ± 3.1	5.0 ± 1.4	4.8 ± 1.8

Note: Brazil, NA1 = North America, JP1 = Japan, KR = Republic of Korea, EUW1 = Europe West, RU = Russia, SG2 = Singapore, Malaysia, and Indonesia, VN2 = Vietnam.

3.2. Statistical analysis

3.2.1. Practice hours per day between servers and tiers

The interaction between server and tier explained little variance for these data (F (21,881) = 1.408, $p = 0.105$). However, there are differences between servers (F (7,881) = 5.942, $p < 0.001$) and tiers (F (3,881) = 29.289, $p < 0.001$) in the total ranked practice hours per day. Specifically, all servers, except Japan, practiced more than Russia ($p < 0.001$ – $p = 0.035$). Also, players in the Korean server practice more than those in the Japanese server ($p = 0.035$). When considering the tier of players, Challenger players tended to practice more hours of solo/duo queue than Master ($p < 0.001$) and Emerald I ($p < 0.001$) players. Grandmaster players also had more hours per day of practice than the Master ($p < 0.001$) and Emerald I ($p < 0.001$) players.

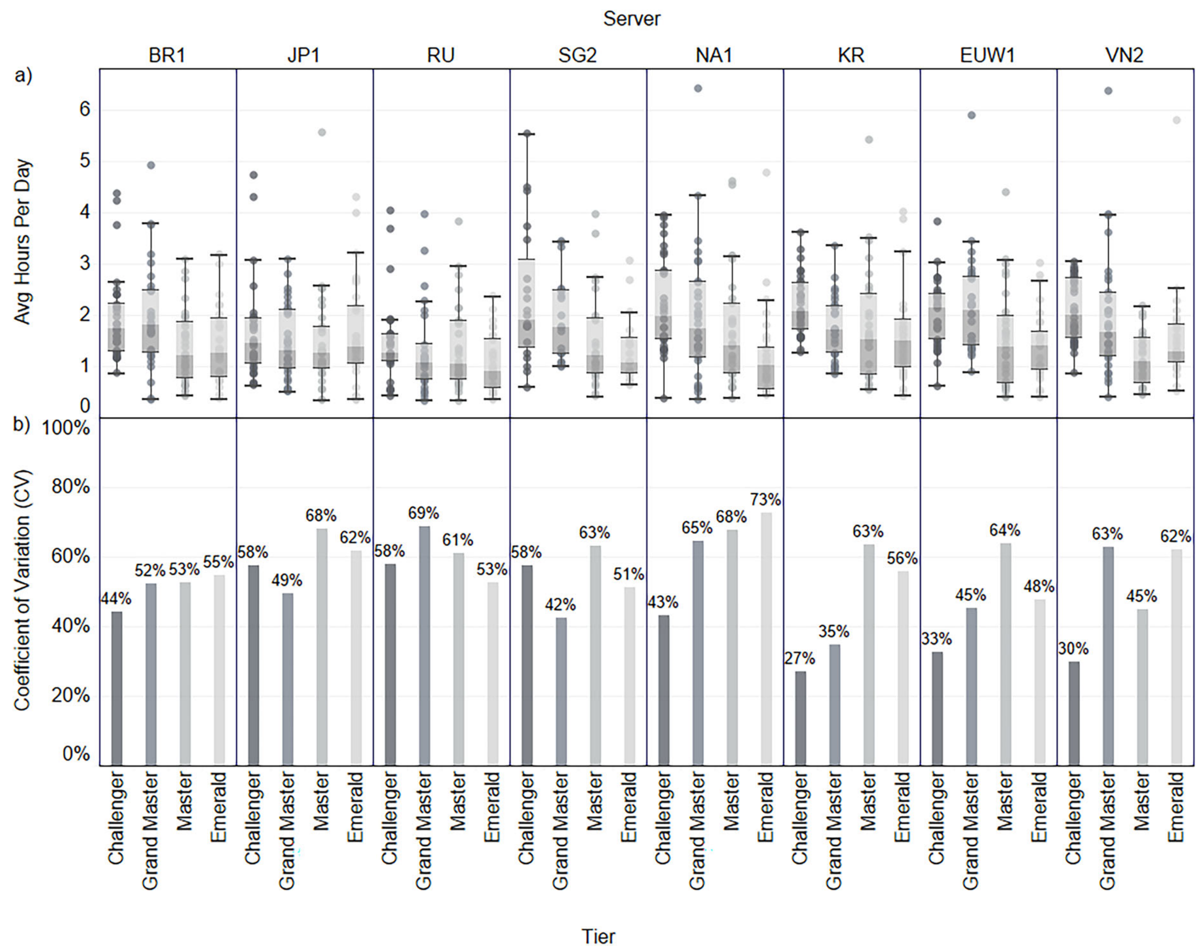

Figure 2. The (a) average ranked solo/duo queue practice hours per day and the (b) associated variability based on server and tier. *Note:* BR1 = Brazil, JP1 = Japan, RU = Russia, SG2 = Singapore, Malaysia, and Indonesia, NA1 = North America, KR = Republic of Korea, EUW1 = Europe West, VN2 = Vietnam.

3.3. Cluster analysis

3.3.1. Identification of practice behaviors

We interpreted the results of the hierarchical cluster analyses and selected four clusters for reporting. These demonstrated easily interpretable patterns of practice using the four metrics. Cluster 1 included larger blocks of practice in relatively short periods and minimal days without play (See Table 4 for specific median and interquartile range values). Cluster 2 displayed shorter blocks of practice than Cluster 1 but with more days without play, resulting in a lower ratio of days practiced to not practiced. Cluster 3 had occasional very large one and three-day blocks, but the player may go many days without practice. Lastly, Cluster 4 included small single and multi-day practice blocks, but somewhat more consistency than Cluster 3.

The proportion of players in each cluster varied depending on the server and tier. Figure 3 displays the breakdown.

4. Discussion

The current exploratory study analyzed preliminary patterns in expert League of Legends players' ranked (solo/duo queue) practice behaviors according to their tier and server. Overall, it appears that greater expertise might be associated with more frequent and consistent daily and weekly practice. Specifically, Challenger players had more matches per day, less variability in daily practice hours, and shorter game durations than other tiers. They also went the fewest days without competing in a match and had the highest number of matches in three- and seven-day blocks than any other tier. The above trends were similar for servers. Those with larger player pools had more daily practice than those with

Table 3. The practice behaviors of league of legends players across servers and tiers.

Server	Tier	Days with at least one match	Most days without a match	Most matches in three days	Most matches in seven days
BR1	Challenger	18.7 ± 5.9	3.5 ± 2.0	29.5 ± 10.1	51.1 ± 15.4
	Grandmaster	17.8 ± 5.8	3.8 ± 2.4	30.9 ± 9.8	50.4 ± 16.6
	Master	20.8 ± 5.0	5.0 ± 2.2	26.8 ± 6.9	45.1 ± 14.1
	Emerald I	22.7 ± 7.8	5.1 ± 1.9	24.5 ± 8.0	41.2 ± 14.6
JP1	Challenger	17.0 ± 6.0	5.5 ± 1.7	34.9 ± 12.0	57.1 ± 18.0
	Grandmaster	19.1 ± 6.9	5.3 ± 1.9	29.0 ± 11.8	47.3 ± 16.2
	Master	20.2 ± 6.7	5.2 ± 2.1	28.7 ± 7.8	47.2 ± 15.4
	Emerald I	20.7 ± 8.0	4.8 ± 2.0	26.4 ± 10.3	43.4 ± 15.4
RU	Challenger	20.3 ± 6.7	5.3 ± 2.1	29.9 ± 8.8	47.3 ± 11.8
	Grandmaster	23.2 ± 8.5	5.3 ± 2.2	25.7 ± 9.5	40.9 ± 12.3
	Master	22.8 ± 8.0	5.6 ± 1.7	26.8 ± 9.5	42.3 ± 15.2
	Emerald I	22.8 ± 7.1	6.1 ± 1.6	25.3 ± 10.1	43.3 ± 17.3
SG2	Challenger	16.6 ± 6.6	3.3 ± 2.5	34.8 ± 8.1	58.4 ± 19.9
	Grandmaster	18.1 ± 6.3	4.2 ± 2.0	31.2 ± 10.8	51.7 ± 16.4
	Master	21.2 ± 7.3	5.2 ± 2.1	27.0 ± 9.3	44.2 ± 16.8
	Emerald I	23.3 ± 9.4	5.4 ± 2.0	24.9 ± 7.3	38.4 ± 11.0
NA1	Challenger	15.9 ± 5.0	3.5 ± 2.0	32.6 ± 9.5	55.1 ± 4.1
	Grandmaster	17.8 ± 6.7	4.0 ± 2.1	30.8 ± 10.2	49.9 ± 14.5
	Master	22.0 ± 10.1	4.7 ± 2.4	27.3 ± 10.7	45.1 ± 17.9
	Emerald I	25.0 ± 7.0	5.6 ± 2.0	22.8 ± 6.3	38.6 ± 12.0
KR	Challenger	13.9 ± 3.6	3.8 ± 1.5	33.0 ± 7.2	56.4 ± 13.5
	Grandmaster	16.8 ± 5.4	4.4 ± 1.7	31.3 ± 10.8	49.6 ± 14.4
	Master	17.4 ± 6.8	5.0 ± 2.0	30.3 ± 21.1	53.2 ± 21.1
	Emerald I	17.9 ± 6.7	5.3 ± 1.8	30.0 ± 10.1	47.0 ± 15.4
EUW1	Challenger	18.3 ± 5.6	3.1 ± 1.3	28.4 ± 8.5	49.9 ± 12.2
	Grandmaster	15.6 ± 4.2	3.7 ± 1.8	30.9 ± 9.0	52.9 ± 16.5
	Master	21.0 ± 7.1	5.1 ± 2.1	26.9 ± 8.7	44.5 ± 15.7
	Emerald I	21.7 ± 5.4	5.2 ± 2.0	25.5 ± 7.4	41.6 ± 11.3
VN2	Challenger	15.3 ± 4.2	4.0 ± 1.9	34.8 ± 10.7	54.9 ± 12.9
	Grandmaster	17.2 ± 7.4	4.4 ± 2.2	31.6 ± 11.5	52.3 ± 17.6
	Master	21.9 ± 7.2	5.8 ± 1.5	27.5 ± 10.2	43.8 ± 14.4
	Emerald I	22.8 ± 6.6	4.7 ± 2.0	23.8 ± 7.9	41.4 ± 14.3

Note: Brazil, NA1 = North America, JP1 = Japan, KR = Republic of Korea, EUW1 = Europe West, RU = Russia, SG2 = Singapore, Malaysia, and Indonesia, VN2 = Vietnam.

Table 4. The practice characteristics of each cluster (median and interquartile range).

Cluster	One day practice block	Three-day practice block	Days without practising	Practice:No practice ratio
1	16 (14–20)	38 (30–44)	2 (1–2)	7.5 (4.6–10.0)
2	13 (11–15)	28 (24–32)	3 (3–4)	3.8 (2.9–5.0)
3	16 (14–18)	32 (27–38)	7 (6–7)	1.0 (0.6–1.5)
4	10 (9–11)	20 (17–23)	6 (5–7)	1.4 (0.8–2.3)

smaller ones. Readers should interpret our findings cautiously as they are based largely on a descriptive analysis, and we recommend that future research use confirmatory methods to test the hypotheses outlined in this article. Nonetheless, the present study contributes to the ongoing theoretical discourse on expertise development in traditional sports and esports, aligning with suggestions that the amount of practice is associated with expert performance. Our study also acts to enhance the methodological rigor of future expertise research by demonstrating a novel approach to overcoming the limitations of retrospective recall through data scraping from a game publisher's API.

4.1. Quantity of practice

The first hypothesis derived from our analyses is that the volume of solo/duo ranked practice is likely associated with expertise. We have centered this hypothesis on the observation that the Challenger and Grandmaster players had significantly more daily solo/duo ranked practice than Master and Emerald I players. Furthermore, Challenger players had the most matches in three- and seven-day blocks. Our finding aligns with previous work in esports. Namely, Pluss et al. (2022) reported that professional Counter-Strike: Global Offensive players had more hours of total and competitive practice than those at a semiprofessional level. Some researchers have also observed similar findings in traditional sports. For example, the time spent in team practice was the most consistent discriminator between elite and sub-elite soccer players (Ward et al., 2007). Likewise, experts in team ball sports accumulated more

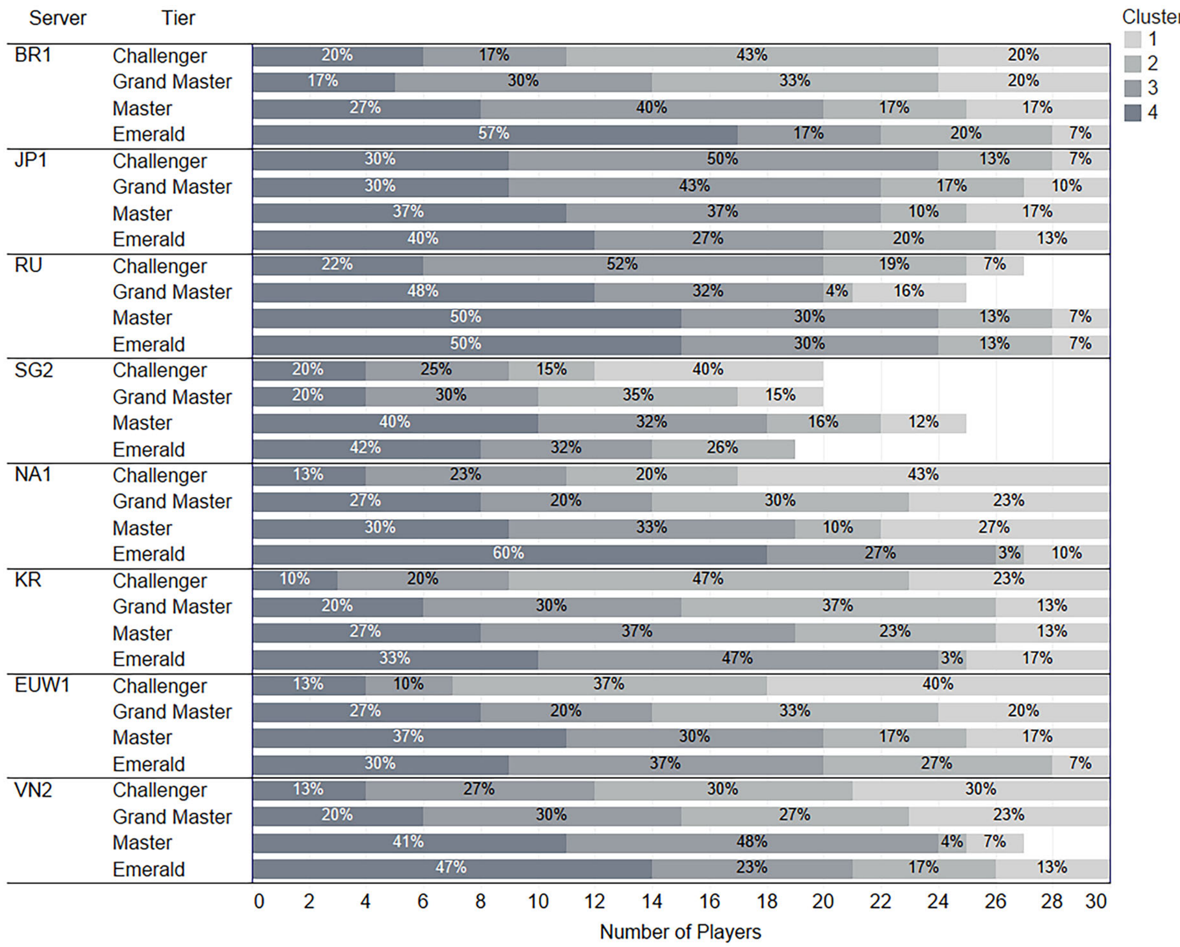

Figure 3. The distribution of practice clusters according to server and tier. *Note:* BR1 = Brazil, JP1 = Japan, RU = Russia, SG2 = Singapore, Malaysia, and Indonesia, NA1 = North America, KR = Republic of Korea, EUW1 = Europe West, VN2 = Vietnam.

hours of sport-specific practice than non-experts after childhood (Baker et al., 2003). Despite this, we note that practice only sometimes discriminates between expertise groups. Ford et al. (2009) observed soccer play activities (not practice) during childhood to differentiate between elite players who attained a professional status and those who did not. Consequently, more research is necessary to better understand the relationship between practice volume and expertise in esports.

4.2. Practice hours variability

A second observation was that the Challenger players had less variability in the total daily practice hours. We hypothesize that this may be due to more effective stress-coping strategies, as previous research has indicated that esports players frequently experience competitive stressors (Leis et al., 2024; Poulus et al., 2022). Higher-skilled players in our sample may have developed more adaptive coping strategies, allowing them to be less affected by negative emotions (e.g., anger and frustration) that could lead to disengagement from the game. For example, Poulus et al. (2020) found that higher in-game ranks were associated with higher mental toughness levels and higher mental toughness levels were associated with more adaptive use of stress-coping strategies. It is also possible that the higher-skilled players, such as those in the Challenger tier, were members of professional organizations with access to psychological support and training, as it is common for these individuals to use ranked practice to complement their team training (Poulus et al., 2022a, 2022b). Finally, it might be that Challenger players have better communication skills, thus overcoming some common team-related stressors, such as communication issues, unfavorable plays, and intra-team conflict (Leis et al., 2024). Future research could build on our findings by examining the factors related to disengagement patterns.

4.3. Practice behavior and player pool size

Our third hypothesis is that there is an interrelationship between player pool size, competitiveness, and practice behaviors. Within our sample, players from relatively large servers had more daily practice hours than those on relatively small servers. We would expect differences in practice behaviors based on server size, as larger servers have more players contesting ladder positioning within a tier. Hence, players will likely need more high-quality practice to outperform their peers, increasing the competitiveness of the server. It could also be that relatively large servers are situated in major regions with an established professional environment, better financial and logistical infrastructure, and higher-quality coaching and support services. These influences would trickle down into ranked match play as the professional players incorporate the game mode into their practice schedules. In other words, more investment into the development of players would make them more skillful, meaning that amateur players participating in ranked matches have tougher competition, thus improving their own skill levels. Future research could relate the number of players within a tier to the performance required to “climb” the competitive ladder.

4.4. Patterns in practice behavior

Our final hypothesis is that there are distinct patterns of practice that promote sustained participation and prolonged disengagement; however, these might not be related to expertise, as there was considerable variability in the relative distribution of each cluster. We suggest that characteristics of Cluster 2 might represent the healthiest engagement with League of Legends solo/due ranked practice because it was characterized by the most consistent participation with limited blocks of excessive hours. It also may not compromise performance (albeit this was not assessed), with nearly half of Korean challenger players displaying this pattern. As we have previously noted, Korea has historically been one of the most successful regions in the professional scene. In contrast, there were two types of practice behavior (i.e., Cluster 1 and 3) that might lead to negative outcomes. Burnout might be most likely in players who display the practice patterns of Cluster 1, with previous research highlighting a relationship between higher volumes of practice and burnout dimensions (Poulus et al., 2024a, 2024b). Furthermore, players in Cluster 3 demonstrated binge-like behaviors. In other words, they would practice excessively for a short period, then disengage for several days before repeating the pattern. Finally, while Cluster 4 might also feature a pattern of healthy engagement, it might compromise performance due to a lower learning stimulus than Cluster 2. According to our findings, there are several avenues for future research. These include examining the relationship between the practice behaviors of Cluster 2, health, and performance; investigating the link between excessive practice and burnout; and determining the association between binge-like practice and prolonged disengagement.

4.5. Theoretical and methodological implications

The present study contributes to the ongoing theoretical discourse on expertise development by offering objective data on the ranked practice behaviors of highly skilled esports players. Although exploratory in nature, our findings align with suggestions that the amount of practice contributes to expertise development and expert performance. It also appears that the consistency of a player’s practice schedule may influence expert performance, although this hypothesis still requires more empirical support. Moreover, our study advances the methodological rigor of expertise research by showcasing a method to address the limitations of retrospective recall techniques through data scraping from a game publisher’s API.

4.6. Strengths and limitations

To our knowledge, the present study is one of the first to action recommendations for research to use a game developer's data repository to explore expertise in esports (Campbell et al., 2018; Pluss et al., 2019). One strength of our study was that we could analyze players' practice histories using objective data that the game client records while a match takes place instead of relying on retrospective recall techniques. As such, we could reduce the chance of biases and estimation errors within our dataset. However, we note that we had to assume that these objective data were error-free or that the errors were randomly distributed, as we were not involved with collecting these data. A second strength of our study was that we analyzed a representative sample of highly skilled esports players, accessing data across four tiers and eight servers. This approach allowed us to hypothesize about the relationship between expertise and practice more confidently. Notwithstanding the strengths of our investigation, there are some noted limitations. First, as we have alluded to throughout this manuscript, the analyses were primarily descriptive, meaning we could only document the patterns within these data. Second, the query limits associated with the API restricted the total sample size and the amount of data we could reasonably access per player. Accordingly, we only sampled a maximum of 30 players per tier and retrieved approximately 10% of their available matches. A third limitation is that we only examined the trends in players' ranked solo/duo practice behaviors. As such, the values recorded in the current manuscript are unlikely to represent to total practice volume, as players might engage in other game modes (e.g., quickplay normal, draft normal, ranked flex, ARAM, etc.). Readers should consider these limitations when drawing conclusions from our manuscript.

5. Conclusion

Despite the descriptive nature of our investigation, our study is among the first to provide preliminary evidence to support the notion that expertise is associated with practice behaviors in esports. We identified distinct patterns in the ranked practice profiles of highly skilled players, revealing more frequent, consistent, and efficient practice routines. Specifically, players in higher tiers engaged in more daily practice with less variability in their total hours and experienced shorter game durations. Additionally, we suggest that players on servers with larger participation pools may require more practice to achieve higher ranks due to greater competitiveness. Finally, we proposed that there are some practice patterns that promote positive engagement with League of Legends and others that may lead to disengagement. While our study was exploratory, it highlights the need for future confirmatory research to test our hypotheses. By analyzing additional data within the repository or employing longitudinal methods, subsequent studies may validate or expand upon our findings.

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Data availability statement

The data supporting this study's findings are available from Riot Games. Restrictions apply to the availability of these data, which were used under license for this study. Data are available from the authors with permission from Riot Games.

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