**Title:** Psychological predictors of long-term esports success: A Registered Report

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**Data sharing**

The data, R code, and materials are openly available at <https://osf.io/zevng/>.

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**Authors' contributions**

MM: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Resources, Writing - Original Draft, Writing - Review & Editing. VMK: Conceptualization, Methodology, Writing - Original Draft, Writing - Review & Editing. YJ: Investigation, Writing - Review & Editing. MA: Methodology, Formal analysis, Data curation, Writing - Review & Editing.

\* MM and VMK are joint first authors of this study

**Conflict of interest**

VMK is one of the PCI RR recommenders.

**Abstract**

The competitive play of digital games, esports, has attracted worldwide attention of hundreds of millions of young people. Although esports players are known to practice in similar ways to other athletes, it remains largely unknown what factors contribute to high performance and to what degree. In the present confirmatory study, our goal is to test whether deliberate practice theory, which has successfully been applied to other sports earlier, can also predict high esports performance. In addition, based on current theory and pilot findings, we predict several gaming-related, personality, and cognitive variables to play crucial roles in long-term esports success. The results will be useful for esports teams, coaches, and all individuals pursuing success in esports.

Keywords: esports; gaming; performance; expertise; competitive

The competitive play of commercial games, esports, has reached a point where masses of young people around the world now pursue careers as esports players. As in any athletic domain, the competition for professional and semi-professional esports careers is extreme. A popular esports game, such as League of Legends, can currently host more than 125 million monthly active players. In this context, becoming an esports professional, semi-professional, or even a high-level amateur has become a contested path—with many major individual and societal implications (e.g., Jin, 2021; Meng-Lewis et al., 2022). Along these events, a relevant research question has emerged: what skills and attributes are needed to become a successful esports player? This is our preliminary research question, which we further specify below.

For decades, it has been known that numerous psychophysical and environmental factors collectively influence expertise development in various fields, such as art, science, and sports (e.g., Bloom, 1985). There are no reasons to suggest that esports is an exception. In each field, however, specific demands influence the ratio between expertise-contributing factors. One of the most popular psychological perspectives to these factors is “deliberate practice,” which Ericsson (2007, p. 14) defines as follows:

”When individuals engage in a practice activity (typically designed by their teachers), with full concentration on improving some aspect of their performance, we call that activity *deliberate practice.* The requirement for *concentration on improving performance* sets deliberate practice apart from both mindless, routine performance and playful engagement”.

Later, deliberate practice with expert feedback has also been conceptually distinguished from “purposeful practice” (not informed by expert knowledge) and “naive practice” (not driven by deliberate skill development) (Ericsson & Pool, 2016). We return to these conceptual differences later.

Recent meta-analyses have found deliberate practice as a stable (but not the *exclusive*) predictor of expertise. On sub-professional levels, deliberate practice has been found to account for 18% of the variance in sports performance (Macnamaraet al., 2016), for 24% of the variance in habitual gaming performance (Macnamaraet al., 2018), and for 37% of the variance in music performance (Platz et al., 2014). Tentative studies suggest that deliberate practice is, indeed, an important factor in different gaming domains too (Boot et al., 2016; Ericsson et al., 2014; Towne et al., 2016). Apart from deliberate practice, other factors have also been proposed to be important in various expert areas; for instance, developmental factors, genetic factors, and psychological factors have gathered mixed evidence across domains (Hambrick et al., 2020; Macnamara, et al., 2016). In the present study, our goal is to test if the deliberate practice theory of performance development applies to esports, and how other psychological, demographic, and environmental components might also contribute to long-term esports success.

As for respective esports types, the total set of demands can be expected to differ (Annika et al., 2022; Koban & Bowman, 2020; Vahlo & Karhulahti, 2020). Whereas success in fast paced titles should be related to motoric accuracy and speed (e.g., StarCraft), other types of esports can be static in a chess-like manner (e.g., Hearthstone) or essentially based on communication via teamwork (e.g., Counter-Strike), thus setting different development and performance criteria. Next to such everyday rationales, there is little confirmatory, empirical research on the factors that are associated with competitive esports success. That work would be valuable for at least three reasons: 1) knowledge of success factors can be useful for professional and semi-professional esports teams and their coaches, 2) open knowledge of esports-specific success factors can provide a more even playing field around the world, and 3) considering that millions of young people are currently playing esports and potentially pursuing professional careers, scientific knowledge of success factors can help them in important career choices.

One of the challenges in interpreting the current literature is that “performance”, as a construct, is rarely delineated temporally (see Sharpe et al. 2022). In other words, while some factors might contribute to one’s performance in the moment (e.g., drinking a cup of coffee), they may not contribute to one’s performance in the long run (unless reconceptualized and remeasured, e.g., coffee drinking habit). Thus, two types of “outcome performance”—i.e. success—should be distinguished: short-term and long-term. *Short-term success*, which is not measured in the present study, is related to momentary performance such as match outcome prediction (Hodge et al., 2021; Smithies et al., 2021). *Long-term success* is related to sustained performance, as represented by rankings and league or tournament outcomes. As an example, previous work has suggested that exercise might improve short-term success (De Las Heras et al., 2020), but there is no evidence for such effects on long-term success. Existing research on long-term success is currently very limited (Table 1), and generally not having taken into account the simultaneous impact of multiple (psychological, environmental, and other) variables—including deliberate practice—which is the focus of the present study.

**Literature on Esports Expertise**

Esports-specific theoretical models of performance have been proposed by Nagorsky and Wiemeyer (2020) and Larsen (2022). Nagorsky and Wiemeyer (2020) combine models of game competencies and sport performance, represented by seven dimensions: tactical-cognitive abilities (e.g, action-planning, strategic thinking), coordination/skill (e.g., eye-hand coordination, spatial perception), psychic or mental abilities (e.g., emotional stability, stress control), social abilities (e.g., cooperation, communication), condition (e.g., endurance, body flexibility), constitution (e.g., age, health state), and media competencies (e.g., ability to deal with technical problems, media knowledge). Because different titles may require different skill sets, the authors draw attention to possible performance profiles. Larsen’s (2022) theory, likewise, suggests seven strands: knowledge about game objects, insights into game systems, understanding metagaming, reading the opponent, ability to execute, emotional discipline, and team coherency.

One meta-analysis on the correlational effects of gaming (not esports) expertise and cognitive abilities (Sala et al., 2018) reported weak relationships between skill and visual attention/processing (r = .07), spatial ability (r = .24), cognitive control (r = -.16), memory (r = .05), and intelligence/reasoning (r = .14). Regarding gender, when controlling for a number of matches, Ratan et al. (2015) found only a negligible skill difference (d = 0.03) between male and female players of League of Legends. We did not find any meta-analyses regarding the relationship between long-term esports success and correlating factors. Three systematic reviews should be also mentioned, however. In the review by Toth et al. (2020), the authors hypothesize that attention, memory, information-processing, and task-switching are also important in esports performance. Pedraza-Ramirez et al. (2020), in turn, focus on the effects of gaming on cognitive variables but also report mixed evidence for the role of practice and age in esports performance. Evidence for the relationship between competitive gaming and psychological (state anxiety, threat evaluations) or physiological stress (change in blood pressure, heart rate, cortisol, or testosterone) is either inconclusive or not supporting this relationship (Leis & Lautenbach, 2020). To map out the literature on long-term performance explicitly, we carried out a systematic database search (Appendix 3, https://osf.io/9tbdy), the results of which are summarized in Table 1.

**Table 1**

*Relationships between long-term esports success and environmental, psychological, and other factors*

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| --- | --- | --- | --- | --- | --- |
| Study | Study sample | Esports performance variable | Correlate | Effect size | Notes |
| Thompson et al. (2013) | 3360 Starcraft 2 players | game rank | actions per minute(1); selection of hotkeys(2); perception action cycles(3); assignments to hotkeys(4); action latency(5) |  | report the different importance of 16 variables for different rank groups. Variable importance for the whole Bronze-Professional group indicated in brackets. |
| Bonny et al. (2016) | 396 MOBA players | Matchmaking Ranking | total playtime | r = .409 | players with higher Matchmaking Ranking spent more hours playing Dota |
| Bonny et al. (2016) | 396 MOBA players | Matchmaking Ranking | age | r = .184 | players with higher Matchmaking Ranking were older |
| Bonny et al. (2016) | 396 MOBA players | Matchmaking Ranking | cognitive performance (number task accuracy) | r = .242 | number task (reaction time) was non-significant with r = -.105 |
| Kokkinakis et al. (2017) | 56 LoL players | game rank | fluid intelligence | rs = .44 | players with higher rank had higher score in WASI II Matrix Reasoning Subtest |
| Kokkinakis et al. (2017) | 8743 Battlefield 3 players | Matchmaking Ranking | age | d = .4 | 22–27 year old group had better performance than 28  years and over group |
| Kokkinakis et al. (2017) | 1669 Destiny players | Matchmaking Ranking | age | d = .45 | 22–27 year old group had better performance than 28  years and over group |
| Kokkinakis et al. (2017) | 286 Dota 2 players | Matchmaking Ranking | age | d = .38 | 22–27 year old group had better performance than 28  years and over group |
| Kokkinakis et al. (2017) | 17861 LoL players | Matchmaking Ranking | age | d = .17 | 22–27 year old group had better performance than 28  years and over group |
| Mora-Cantallops & Sicilia (2018) | 547 LoL players | player’s rank | competence | NA | measured with The Player Experience of Need Satisfaction scale |
| Mora-Cantallops & Sicilia (2018) | 547 LoL players | player’s rank | presence (immersion) | NA | measured with The Player Experience of Need Satisfaction scale |
| Stamatis et al. (2019) | 23 esports players | average place on Fortnite: Solo matches over 3-hours | physical exercise | NA | players with higher placement spent more days of exercise per week |
| Hulaj et al. (2020) | 329 Dota 2 players | Matchmaking Ranking | total number of games played | r = .59 | players with higher Matchmaking Ranking play more Dota games |
| Hulaj et al. (2020) | 329 Dota 2 players | Matchmaking Ranking | motivation: integrated regulation | r = .18 | players with higher Matchmaking Ranking have higher integrated regulation motivation |
| Hulaj et al. (2020) | 329 Dota 2 players | Matchmaking Ranking | basic need: competence | r = .44 | players with higher Matchmaking Ranking felt more competent in the game |
| Hulaj et al. (2020) | 329 Dota 2 players | Matchmaking Ranking | basic need: autonomy | r = .18 | players with higher Matchmaking Ranking experienced more freedom in the game |
| Hulaj et al. (2020) | 329 Dota 2 players | Matchmaking Ranking | basic need: relatedness | r = .12 | players with higher Matchmaking Ranking perceive relationships in the game as more important |
| Li et al. (2020) | 70 LoL players |  | cognitive flexibility (task-  switching costs) | d = −.49; d = −.57; d = −.77 | differences between Bronze:Diamond group and Master and over group in the Stroop-switching  test (three conditions: congruent, neutral, incongruent) |
| Matuszewski et al. (2020) | 206 LoL players | player’s rank | extraversion | ηp2 = .025 | differences between the three lowest (Bronze, Silver, and Gold) and  three highest (Platinum, Diamond, and Master) divisions |
| Matuszewski et al. (2020) | 206 LoL players | player’s rank | agreeableness | ηp2 = .023 | differences between the three lowest (Bronze, Silver, and Gold) and  three highest (Platinum, Diamond, and Master) divisions |
| Matuszewski et al. (2020) | 206 LoL players | player’s rank | openness | ηp2 = .030 | differences between the three lowest (Bronze, Silver, and Gold) and  three highest (Platinum, Diamond, and Master) divisions |
| Trotter et al. (2021) | 1440 adult esports players (mostly playing Overwatch, LoL, CS:GO, Rocket League, and Dota) | four rank categories based on percentages | social support | ηp2 = .02 | small differences found for esteem, emotional, informational, and tangible support |
| Trotter et al. (2021) | 1440 adult esports players (mostly playing Overwatch, LoL, CS:GO, Rocket League, and Dota) | four rank categories based on percentages | self-regulation | ηp2 = .21 | small differences found in triggering, input, searching, planning, and assessing |
| Trotter et al. (2021) | 1440 adult esports players (mostly playing Overwatch, LoL, CS:GO, Rocket League, and Dota) | four rank categories based on percentages | psychological skill use | ηp2 = .37 | small differences found in self-talk, automaticity, goal-setting, imagery, and activation |
| Toth et al. (2021) | 39 CS:GO players | player’s rank | time to shoot, time to destroy, ammo to destroy | NA | high rank (Gold Nova Master – Global Elite) had better performance (less seconds, ammo) than low rank group (Silver 1 – Gold Nova 3) |

Additionally, we found four qualitative studies that reported interviews with high-level esports players. For Overwatch, the relevance of game sense and mechanics were highlighted (Fanfarelli, 2018). For League of Legends, strategic thinking, game knowledge, decision making, motivation, attention, warm-up, communication, adaptability, team dynamics, replays, and practice were highlighted (Himmelstein et al., 2017) (regarding the effectiveness of these activities, see also Abbott et al., 2022). For both above esports, factors such as practice conditions, coping with stress, emotion regulation, team cohesion or presence of a coach were also suggested (Poulus et al., 2022). In addition to the often proposed mechanical expertise, Donaldson (2015, p. 440) further suggested the importance of so-called metagame expertise, defined more broadly as an awareness of all unique details and contexts around the game, such as ”formulation of new strategies after a patch, the use of mathematical techniques to determine the effectiveness of a particular item or ability combination.“ Many of the above factors have also been identified in phenomenological qualitative work on esports (Karhulahti, 2020; Witkowski, 2012). Based on this reviewed literature, it seems possible that various psychological, environmental, and game-related factors correlate with long-term esports success, and these factors might differ between esports titles. In order to formulate informative hypotheses, we carried out two pilot studies based on the literature.

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* Pilot 1 was carried out to confirm and elaborate on the effects reported in the empirical and theoretical literature. We surveyed 351 players (88.3% males) with a mean age of 21.59 from multiple esports titles and asked them to rate 25 variables extracted from the existing literature. The five most important variables in MOBA games (League of Legends and DotA 2) were strong will, attention, speed of decision-making, good teammates, resilience, and self-confidence and in FPS games (Counter-Strike: Global Offensive, Tom Clancy's Rainbow Six: Siege, and Overwatch) the five most important were attention, speed of decision-making, good teammates, resilience, self-confidence, and persistence. We also included open-ended questions and instructed the participants to rank variables they consider most important for esports success; the ranked variables were then clustered and quantified. Based on this analysis, the five most important variables among MOBA players were self-control, persistence, teamwork, mechanical skill, and game sense and among FPS players persistence, teamwork, mechanical skill, game sense, and resilience. For the data and detailed results, see Appendix 1 (https://osf.io/57dzm/).
* Pilot 2 was carried out to form a testable model based on the literature and Pilot 1. We selected 28 predictors, which were measured in two participant groups (*N1* = 290 from Counter-Strike: Global Offensive and *N2* = 284 from League of Legends, with a mean age of 24.9 and 24.5 years who self-identified as esports players). Long-term performance in esports was based on in-game ranking and measured as the highest rank achieved in the last 12 months. The significance of the predictors within the models differed between the two titles. Descriptive statistics and summarized results of hierarchical regression analysis are presented in Table 2 and 3. For the data and detailed results, see Appendix 2 (https://osf.io/qbd7x/).

**Table 2**

*Descriptive statistics from Pilot 2 data*

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|  | Counter-Strike: Global Offensive (*N1* = 264) | | League of Legends (*N2* = 231) | |
|  | *M* | *SD* | *M* | *SD* |
| rank | 12.25 | 4.66 | 15.45 | 5.08 |
| practice (hours) | 2.85 | 1.89 | 3.06 | 1.81 |
| deliberate practice (hours) | 1.35 | 1.70 | 1.32 | 1.70 |
| title-specific career length (years) | 8.22 | 4.39 | 7.20 | 2.61 |
| physical training (minutes) | 52.70 | 41.18 | 50.11 | 46.92 |
| attention (ms) | 935.29 | 203.89 | 958.35 | 226.65 |
| decision-making (successful stops %) | 77.88 | 17.31 | 77.84 | 17.51 |
| reaction time (ms) | 265.68 | 45.56 | 274.77 | 35.69 |
| team work (scale 8-40) | 31.00 | 4.67 | 30.75 | 4.41 |
| intelligence (scale 0-6) | 3.94 | 1.53 | 3.99 | 1.48 |
| persistence (scale 5-25) | 14.10 | 2.48 | 13.45 | 2.82 |

**Table 3**

*Effect sizes derived from Pilot 2 and the smallest effect sizes of interest (SESOI) for confirmatory analysis (for justifications, see Appendix 5* (<https://osf.io/2nrqb>).

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| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | Counter-Strike: Global Offensive  [CSGO] (18 ranks) | | | | | League of Legends  [LoL] (27 ranks) | | | | |
|  | *β* | *β* 95% CI | *B* | *β*/ *B* zero-order | 95% CI for *β* zero-order | *β* | *β* 95% CI | *B* | *β*/*B* zero-order | 95% CI for *β* zero-order |
| practice | **.18** | **.04, .31** | **.43** | **.29/.71** | **.16, .41** | .10 | -.26, .07 | .29 | **.25/.70** | **.09, .41** |
| CSGO, SESOI r = .3 -> an increase of practice by 1 hour per day would increase rank by .73  LoL, SESOI r = .2 -> an increase of practice by 1 hour per day would increase rank by .56 | | | | | | | | | | |
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| deliberate practice | -.05 | -.18, .08 | -.13 | .08/.23 | -.05, .21 | .13 | -.01, .27 | .38 | **.26/.78** | **.15, .37** |
| CSGO, SESOI r = .3 -> an increase of deliberate practice by 1 hour per day would increase rank by .78  LoL, SESOI r = .2 -> an increase of deliberate practice by 1 hour per day would increase rank by .60 | | | | | | | | | | |
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| attention | **-.17** | **-.31,-.03** | **-.004** |  |  | -.01 | -.12, .09 | -.0003 |  |  |
| CSGO, SESOI r = .3 -> a decrease of response time by 1ms would increase rank by .007  LoL, SESOI r = .2 -> a decrease of response time by 1ms would increase rank by .006 | | | | | | | | | | |
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| decision-making | .11 | -.01, .23 | .03 |  |  | .10 | -.00, .20 | .03 |  |  |
| CSGO, SESOI r = .3 -> an increase of successful stops in nogo trials by 1 percent would increase rank by .08  LoL, SESOI r = .2 -> an increase of successful stops in nogo trials by 1 percent would increase rank by .06 | | | | | | | | | | |
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| reaction time | -.16 | -.34, .02 | -.02 |  |  | **-.14** | **-.28, -.00** | **-.02** |  |  |
| CSGO, SESOI r = .3 -> a decrease of reaction time by 1 ms would increase rank by .04  LoL, SESOI r = .2 -> a decrease of reaction time by 1 ms would increase rank by .03 | | | | | | | | | | |
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| teamwork | .02 | -.13, .17 | .02 |  |  | **.13** | **.00, .25** | **.15** |  |  |
| CSGO, SESOI r = .3 -> an increase of teamwork (total score ranging from 8 to 40) by 1 would increase rank by .3  LoL, SESOI r = .2 -> an increase of teamwork (total score ranging from 8 to 40) by 1 would increase rank by .23 | | | | | | | | | | |
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| intelligence | .10 | -.02, .22 | .31 |  |  | .12 | -.02, .25 | .40 |  |  |
| CSGO, SESOI r = .3 -> an increase of intelligence score (total score ranging from 0 to 6) by 1 would increase rank by .93  LoL, SESOI r = .2 -> an increase of intelligence score (total score ranging from 0 to 6) by 1 would increase rank by .70 | | | | | | | | | | |
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| persistence | .02 | -.14, .19 | .04 |  |  | .11 | -.05, .27 | .20 |  |  |
| CSGO, SESOI r = .3 -> an increase of persistence (total score ranging from 5 to 25) by 1 would increase rank by .6  LoL, SESOI r = .2 -> an increase of persistence (total score ranging from 5 to 25) by 1 would increase rank by .36 | | | | | | | | | | |
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| age | **-.24** | **-.37, -.12** | **-.20** |  |  | **-.23** | **-.37, -.09** | **-.24** |  |  |
| CSGO, SESOI r = .3 -> a decrease of age by 1 year would increase rank by .24  LoL, SESOI r = .2 -> a decrease of age by 1 year would increase rank by .21 | | | | | | | | | | |

*Note*: significant predictors at alpha level of .05 highlighted with bold. Model does not include all variables. Practice was measured using the item “How many hours per day on average do you play [GAME NAME]?” Deliberate practice was measured using the item: “Of all the time that you spend on esports, how many hours per day on average consist of deliberate practice, i.e. activities that need focused attention and aim at improving specific esports skills?” Arguably, this item measures both “purposeful” and “deliberate” practice, but see our discussion regarding this overlap below. Zero-order estimates are likely more informative for practice and deliberate practice because current evidence implies both to operate as colliders for many of our other predictors. Purple is used for variables where null is hypothesized; green signals the alternative hypothesis (for justifications, see Appendix 4 at https://osf.io/cyg3f).

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Based on the pilot work above, we set the following hypotheses to be tested on three separate samples with participants from different esports games: League of Legends, Counter-Strike: Global Offensive, and Fortnite. Tests with Fortnite are exploratory due to lack of game-specific pilot data. In all groups, esports performance is measured by the participants’ peak ranking in the past year. For the purposes of the present study, we define *meaningful effect* as the smallest visible indicator of rank change with reasonable and possible improvement in the variable (Table 3). For a detailed rationale of each hypothesis, we refer to Appendix 4 (https://osf.io/cyg3f).

**H1:** Following the pilot results and theory, we expect that

* **H1a** (CSGO, LoL)higher quantity of naive *practice* will meaningfully predict long-term esports success, and
* **H1b** (LoL)higher quantity of*deliberate practice*will also meaningfully predict long-term esports success.
* **H1c** (CSGO) higher quantity of *deliberate practice* will predict long-term esports success, but not to a meaningful extent.

**H2:** Following the pilot results and previous empirical evidence, we expect the following psychological and other factors to *meaningfully* predict long-term esports success:

* **H2a** (CSGO, LoL) better (lower) reaction time,
* **H2b** (LoL) higher teamwork ability,
* **H2c** (LoL) higher intelligence, and
* **H2d** (LoL) higher persistence
* **H2e** (CSGO, LoL)younger age
* **H2f** (CSGO) better attention (lower response time)

In turn, we expect the following psychological and other factors to contribute to long-term esports success *not meaningfully* or *at all* (null):

* **H2g** (LoL) attention
* **H2h** (CSGO, LoL) speed of decision making,
* **H2i** (CSGO) teamwork ability,
* **H2j** (CSGO) intelligence, and
* **H2k** (CSGO) persistence.

For statistical interpretations of each hypothesis, see the Design section below. We will not deem H1 or H2 (not) corroborated in general but each sub-hypothesis independently.

***Games description***

To extend the generalizability of our results and to compare the relative contribution of our predictors across different games—with arguably varying mechanical and psychological demands—we use data from three games. League of Legends, Counter-Strike: Global Offensive, and Fortnite are currently the top three of the most impactful PC Esports games based on The Esports Observer’s impact index (Seck, 2021).

League of Legends is a MOBA (Multiplayer online battle arena) game developed and published by Riot Games in 2009. While League of Legends offers several gameplay modes and maps, the flagship mode is player-versus-player (5 vs 5) combat in the Summoner’s Rift map from an isometric perspective. Each match begins with two opposing teams occupying half of the map. The players collaborate as a team to achieve the ultimate victory condition, of destroying the opposing base’s main structure, Nexus, while protecting their own. Each of the ten players selects and controls a character, known as a "champion" and by 2023, there are approximately 160 champions with unique skills and playing styles. The game demands complex strategic thinking in real-time, integrating loads of high-intensity information, and a degree of mechanical skill on both personal and team levels.

Counter Strike: Global Offensive is a multiplayer tactical first-person shooter released in 2012 and developed by Valve and Hidden Path Entertainment. Two opposing teams, the Terrorists and the Counter-Terrorists, play in successive rounds across different maps. Players are granted game currency based on their performance at the end of each round, which they can use to purchase weapons or utility in later games. In the primary and competitive game mode, two teams of five players compete in a best-of-30 match. The game’s demands largely overlap with League of Legends, with the following two caveats: the information load is not as high as in League of Legends (e.g., due to fewer updates and lack of constantly added new champions), but the significance of motoric accuracy and speed are arguably higher.

Fortnite is a third-person shooter game developed in 2017 by Epic Games. As of 2023, Fortnite features three more separate game modes. Battle Royale is a player-versus-player match for up to 100 players. The players are airdropped in a weaponless condition from a ‘Battle Bus’ that crosses the battlefield. Upon landing, they are required to scavenge for weapons, resources, and items. The elimination match is won by the last person, duo or squad standing. Until the recent addition of Zero Build, Battle Royale has been the primary competitive mode and the participation is based on solo or duo. However, Creative mode also has been employed in the competitive scene, where four-player teams battle in various maps. The demands of Fortnite are very similar to those of Counter Strike: Global Offensive, yet teamwork tends to operate differently and there is an increased element of uncertainty across skill domains due to variation in starting location.

**Methods**

This study received a positive appraisal from the Ethics Committee of the University of Presov.

**Participants**

Survey data will be collected via the Prolific platform. The samples will consist of self-identified esports players—inclusion item: “Are you an esports player? (i.e., playing esports games on ranked levels”)—older than 18 years and playing either League of Legends (Sample 1), Counter-Strike: Global Offensive (Sample 2), or Fortnite (Sample 3). As previous research has shown that many such players engage with several esports simultaneously (Vahlo & Karhulahti, 2022), inclusion to samples will be measured by the item: “What is the name of the esports game you play the most?” According to prescreening, it is estimated that ~15% of the participants will be women and the average age will be 25 years. Our survey will be distributed in English, but we will not control the nationality or language skills of our participants. We generally rely on the data quality of Prolific, but see quality checks below.

The sample size is based on a priori power analysis calculated for power of an individual independent variable in the regression model with our smallest effect size of interest (SESOI) *r* = .3 (CSGO) and *r* = .2 (LoL). These SESOIs are justified in Appendix 5 (<https://osf.io/2nrqb>). Required sample size (*N1* = 143 in CSGO and *N2* = 316 in LoL) was calculated considering the type of statistical analysis (Linear multiple regression: Fixed model, Single regression coefficient, G\*Power; Faul et al, 2007), inclusion of 9 predictors, α = .01, two tailed hypothesis, β = .95, and f2 =.128/.057 calculated from variance explained by predictor (.09/.04) and hypothesized residual variance (.70). We chose the alpha level .01 with 95% power in order to both reasonably minimize error rates and to acknowledge that Type I errors are more serious than Type II errors. Based on our pilot studies, we will oversample *N*1, *N*2, and *N*3 by 10% to allow removing careless respondents (see data quality checks below) and by additional 10% to remove respondents who no longer play ranked games actively (answering positively to: “Have you played GAME NAME in the past 12 months actively on a ranked level?”). For equivalence testing, we will oversample all samples by additional 10%, thus having the final samples of *N1* = 186 and *N2* = 411. We will use the same sample size of *N3* = 186 also for Fortnite.

**Measures**

**Dependent variable**

Long-term success will be based on in-game skill ranking measured by the following item: “In the past 12 months, what is your highest rank in GAME NAME?” with response scale from Iron IV to Challenger (27 unique ranks) for League of Legends, from Silver I to Global Elite (18 different ranks) for Counter-Strike: Global Offensive, and from Open League: Division I to Champion League: Division III (10 unique ranks) for Fortnite. We will also apply alternative operationalizations of in-game skill ranking for exploratory analyses: “During the years of playing GAME NAME, what has been your highest rank ever?”.

**Independent variables**

Practice will be measured by a new instrument specifically developed for this study after the piloting phase (Pilot 3 and Appendix 6, <https://osf.io/n75r3> and Pilot 4 for clarity check, https://osf.io/2g5ys/. The instrument involves items representing “naive practice”, “purposeful practice”, and “deliberate practice”. In this study, for confirmatory hypothesis testing, naive practice is measured only with one item (P4) but for exploratory analyses with all four naive practice items (P1—P4). This decision was made because we found no empirical support for practice types like gym and meditation to improve esports success, unlike gaming experience does (Table 1, Table 3). As for the purposeful and deliberate practice, they have significant conceptual overlap (Ericsson & Pool, 2016). Whereas both are goal-driven, purposefully aiming to improve certain aspects of performance, deliberate practice is “informed and guided by the best performers’ accomplishments” (p. 66). Because we consider the risk of *confusing purposeful practice with naive practice* severe, and quantitatively measuring *whether one’s purposeful practice was properly “informed”* extremely difficult, in this study we will use all four non-naive practice items for assessing deliberate practice, albeit some of them (DP1, DP4) clearly concerns both purposeful and deliberate practice types. Both constructs, “general practice” and “deliberate practice” are calculated by multiplying respective practice time with game-specific career length.

1. **Practice** and
2. **Deliberate practice** will be measured with the following new instrument.

During the past 12 months of playing [GAME NAME], how many *hours per week* did you spend on the following activities?

The first two activities require *focused attention* and *directly* aim at improving **esports rank/skills**.

* [DP1] Learning *alone* (from guides, videos, streams, replays, etc.)? This does **not** include playing.
* [DP2] Learning *with others* (getting feedback from teammates or coaches, team discussions, etc.)? This does **not** include playing.

The next three activities do *not directly* aim at improving **esports rank/skills**.

* [P1] Physical practice (gym, running, etc.)?
* [P2] Mental practice that is **not** playing (meditation, breathing exercise, etc.)?
* [P3] Relaxing esports activities that are **not** playing (watching streams, discussing the game, etc.)

The last activities specifically concern *playing* esports game(s). The first two require *focused attention* and *directly* aim at improving **esports rank/skills**.

* [DP3] Playing with *coaches, team*, or other experts (with tactical communication, reflection, etc.)
* [DP4] Playing the game *alone* (practicing aim or last-hit, game scenarios/matchups, etc.)?

The final activity does *not directly* aim at improving **esports rank/skills**.

* [P4] Routinely playing the game (ranked mode, non-ranked mode, with or without friends, etc.). Please, exclude the hours you reported earlier.

Game-specific career length will be used as a multiplier for the above two practice constructs: “How many years have you played [GAME NAME] **actively**, i.e. with similar or higher intensity as during the past 12 months?”

C) **attention** will be measured using the Visual search task[[1]](#footnote-2) and PsyToolkit software (Stoet, 2010; Stoet, 2017) and operationalized as the average response time across all correct trials (Treisman & Gelade, 1980).

D) **speed of decision making** will be measured using the Stop signal task1 and PsyToolkit software (Stoet, 2010; Stoet, 2017) and operationalized as the percentage of successful stops in nogo trials and for sensitivity analysis as the total number of correct trials (combination of actions without go-omissions and go-errors)

E) **reaction time** will be measured using the Deary-Liewald task1 and PsyToolkit software (Stoet, 2010; Stoet, 2017) and operationalized as the average simple reaction time in correct responses.

F) **teamwork** as a perceived ability to work with others to achieve common goals will be measured using the eight items of the Teamwork Scale (Lower et al., 2015). Items such as ”I am good at communicating with my team members” are rated on a 5-point scale ranging from 1 (not at all true) to 5 (really true).

G) **intelligence** will be measured using six items of the Short Form of the Hagen Matrices Test (HMT; Heydasch et al., 2020). HMT is a figural matrices test that primarily measures induction, reasoning, and fluid intelligence. Items have increasing difficulty and comprise incomplete matrices in which the missing part needs to be identified by recognizing the underlying rule of the depicted pattern.

H) **persistence** “as trait-level perseverance and passion for long-term goals” will be measured using the five items from the Short Grit Scale (Grit–S), (Duckworth & Quinn, 2009, p. 166) consisting of all items from the Perseverance of Effort subscale and one from the Consistency subscale, an item structure proposed by Lechner et al. (2019). Items such as ”I finish whatever I begin” are rated on a 5-point scale ranging from 1 (not at all like me) to 5 (very much like me).

For exploratory analyses, we will also measure other variables (gender, hardware quality, ping, ADHD, gaming disorder, physical training, and team membership). The full survey is available at: https://osf.io/m89x7/.

**Design and analysis plan**

The data will be analyzed by a robust linear regression analysis in R software using the MASS package (Venables & Ripley, 2002) and rlm function with MM method. Equivalence testing will be calculated in each case when SESOI is not met, using the equivalence\_test function with the classic method (following the TOST rule; Lakens, 2017) provided by the parameters library (Lüdecke et al., 2020). Participants with higher than 30% of missing data will be omitted from analyses. Missing data (except demographic data and cognitive variables) will be handled using the chained random forests and the missRanger package (Mayer, 2021).

Because previous research indicates that age and practice may have direct causal effects on attention, decision making, reaction time, and teamwork (e.g., Best & Miller, 2010; Ciuffreda, 2011; Madden 2007; McEwan et al., 2017; Posner et al., 2015), we have a reason to treat the latter as mediators between age  rank and practice  rank. They should thus be modeled separately to avoid producing biased estimates in the respective effects (see Wysocki et al., 2022). Accordingly, we test our hypotheses with two separate regression equations, which are structured to include variables that are unlikely to be mediators or colliders.

E1: practice, deliberate practice, persistence, age, and intelligence

E2: attention, decision-making, reaction time, teamwork, persistence, and intelligence

The effects of intelligence and persistence, which are in both equations, need to meet the SESOI in each model to corroborate respective hypotheses.

We consider H1a–b and H2a,b,e,f,g,h,i (with single-regression variables) corroborated if the point estimate of the effect exceeds r = .3 (with p < .01) in CSGO and r = .2 (with p < .01) in LoL, and null corroborated if equivalence testing (Lakens, 2017) will prove the absence of effect r > .3 in CSGO or r > .2 in LoL. In the case of neither, we deem the results inconclusive. Unlike the above, H1c is corroborated only if we witness an effect r < .3 and equivalence testing does suggest the absence of effect.

We consider H2c,d,j,k (with two-regression variables) corroborated if the point estimate of the effect exceeds r = .3 (with p < .01) in CSGO and r = .2 (with p < .01) in LoL in both regressions, and null corroborated if equivalence testing (Lakens, 2017) will prove the absence of effect r > .3 in CSGO or r > .2 in LoL in both regressions. In the case of neither, we deem the results inconclusive.

We will treat the results for Fortnite as exploratory.

***Outcome-neutral control***

For League of Legends respondents, ranking is measured by icons instead of a text (see https://osf.io/3atnf/). For the players of Counter-Strike: Global Offensive and Fortnite, identical items measuring ranking with response options presented backwards will be used.

***Data quality checks***

To control careless responding we will employ two specific items: 1) Bogus item: ”I have been paid biweekly by green intergalactic leprechauns“ to which respondent should respond using the option “*Not at all true*,” and 2) Instructed response item: ”I always follow activities that will... Ignore the previous part of the question and check “*Mostly like me*.“ In addition to the above two items we will also use Mahalanobis distance statistic. Participants who fail one of the two items *and* at the same time will have Mahalanobis distance statistic higher than the alpha quantile of the chi-square distribution will be omitted from analyses.

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**Study design template**

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
| Question | Hypothesis | Sampling plan | Analysis Plan | Rationale for deciding the sensitivity of the test for confirming or disconfirming the hypothesis | Interpretation given different outcomes | Theory that could be shown wrong by the outcomes |
| **RQ1**: Do the principles of deliberate practice theory apply to esports expertise, as perceived through long-term esports success? | **H1:** Following the pilot results and theory, we expect that:  **H1a** (CSGO, LoL)higher quantity of naive *practice* will meaningfully predict long-term esports success, and  **H1b** (LoL)higher quantity of*deliberate practice*will also meaningfully predict long-term esports success.  **H1c** (CSGO) higher quantity of deliberate practice will predict long- term esports success, but not to a meaningful extent. | Survey data will be collected via the Prolific platform. The samples will consist of self-identified esports players older than 18 years and playing either League of Legends (Sample 1), Counter-Strike: Global Offensive (Sample 2), or Fortnite (Sample 3). The sample size is based on a priori power analysis calculated for power of an individual independent variable in the regression model with our smallest effect size of interest (SESOI) *r* = .3 (CSGO) and *r* = .2 (LoL). These SESOIs are justified in Appendix 5 (<https://osf.io/2nrqb>). Required sample size (*N1* = 143 in CSGO and *N2* = 316 in LoL) was calculated considering the type of statistical analysis (Linear multiple regression: Fixed model, Single regression coefficient, G\*Power; Faul et al, 2007), inclusion of 9 predictors, α = .01, two tailed hypothesis, β = .95, and f2 =.128/.057 calculated from variance explained by predictor (.09/.04) and hypothesized residual variance (.70). Based on our pilot studies, we will oversample *N*1, *N*2, and *N*3 by 10% to allow removing careless respondents (see data quality checks below) and by additional 10% to remove respondents who no longer play ranked games actively. For equivalence testing, we will oversample all samples by additional 10%, thus having the final samples of *N1* = 186 and *N2* = 411. We will use the same sample size of *N3* = 186 also for Fortnite. Tests with Fortnite are exploratory. | The data will be analyzed by a robust linear regression analysis in R software using the MASS package (Venables & Ripley, 2002) and rlm function with MM method. Equivalence testing will be calculated in each case when SESOI is not met, using the equivalence\_test function with the classic method (following the TOST rule; Lakens, 2017) provided by the parameters library (Lüdecke et al., 2020). Participants with higher than 30% of missing data will be omitted from analyses. Missing data (except demographic data and cognitive variables) will be handled using the chained random forests and the missRanger package (Mayer, 2021).  We test our hypotheses with two separate regression equations, which are structured to include variables that are unlikely to have mediating relationships:  E1: practice, deliberate practice, persistence, age, and intelligence  E2: attention, decision-making, reaction time, teamwork, persistence, and intelligence  The effects of intelligence and persistence, which are in both equations, need to meet the SESOI in each model to corroborate respective hypotheses. | Our SESOI is based on a critical discussion of standardized and unstandardized regression coefficients found in Pilot 2 data - on a discussion of how large the change in IV should be to provide meaningful change in DV. We assessed the smallest effect that still has motivational potential = effort to increase performance by one rank. | We consider H1a–b corroborated if the point estimate of the effect exceeds r = .3 (with p < .01) in CSGO and r = .2 (with p < .01) in LoL, and null corroborated if equivalence testing (Lakens, 2017) will prove the absence of effect r > .3 in CSGO or r > .2 in LoL. In the case of neither, we deem the results inconclusive. Unlike the above, H1c is corroborated only if we witness an effect r < .3 and equivalence testing does suggest the absence of effect. | If H1 is corroborated, this will support the applicability of deliberate practice theory in the esports context.  If equivalence testing indicates the null, this suggests that deliberate practice theory does not apply to esports or needs to be modified in the esports context. |
| **RQ2**: What other factors, such as psychological, environmental, and game-related variables, contribute to long-term esports success? | **H2:** Following the pilot results and previous empirical evidence, we expect the following psychological and other factors to *meaningfully* predict long-term esports success:  **H2a** (CSGO, LoL) better (lower) reaction time,  **H2b** (LoL) higher teamwork ability,  **H2c** (LoL)higher intelligence, and  **H2d** (LoL) higher persistence  **H2e** (CSGO, LoL)younger age  **H2f** (CSGO)better attention (lower response time)  In turn, we expect the following psychological and other factors to contribute to long-term esports success *not meaningfully* or *at all* (null):  **H2g** (LoL) attention  **H2h** (CSGO, LoL) speed of decision making,  **H2i** (CSGO) teamwork ability,  **H2j** (CSGO) intelligence, and  **H2k** (CSGO) persistence. | We consider H2a,b,e,f,g,h,i (with single-regression variables) corroborated if the point estimate of the effect exceeds r = .3 (with p < .01) in CSGO and r = .2 (with p < .01) in LoL, and null corroborated if equivalence testing (Lakens, 2017) will prove the absence of effect r > .3 in CSGO or r > .2 in LoL. In the case of neither, we deem the results inconclusive.  We consider H2c,d,j, k (with two-regression variables) corroborated if the point estimate of the effect exceeds r = .3 (with p < .01) in CSGO and r = .2 (with p < .01) in LoL in both regressions, and null corroborated if equivalence testing (Lakens, 2017) will prove the absence of effect r > .3 in CSGO or r > .2 in LoL in both regressions. In the case of neither, we deem the results inconclusive. | If H2 are corroborated, this supports the idea that esports expertise, as defined by long-term success, is produced by various co-contributing variables. |
| [implicit RQ]  **RQ3**: Do the long-term success factors differ between esports titles? | [auxiliary hypothesis, not tested but will be discussed]  We expect that different factors will be relevant in different esports games *–* represented by the name of the game stated in parenthesis in the above hypotheses. | [auxiliary theory]  If we confirm the same variables having effects and null effects in different esports, as tested in H2, this will support the premise that different variables are important for success in different esports games. Null will imply that similar variables are important across esports. |

**Appendix 1: Pilot 1**

Sample

Sample consisted of 351 players (88.3% males) with a mean age of 21.59 years playing one of the following games: League of Legends, Dota 2, StarCraft 2, Counter-Strike: Global Offensive, Tom Clancy's Rainbow Six: Siege, and Overwatch. Players were approached on different gaming forums and platforms such as Discord, Battlenet, reddit or Facebook.

Measures, procedure, and results

Games were grouped into three different game genres, namely RTS games (StarCraft 2), MOBA games (League of Legends, Dota 2), and FPS games (Counter-Strike: Global Offensive, Tom Clancy's Rainbow Six: Siege, and Overwatch).

*Quantitative part*

Participants were asked to rate importance (for esports performance) each of the 25 variables (extracted from theories and literature review) on a scale ranging from 1 – not at all important to 5 – very important. Variables were sorted based on their ratings with higher scores indicating their higher importance for esports success. For each game, ten most important variables were selected for the subsequent exploratory study.

Table 1

*Mean factors importance scores for success in StarCraft 2*

|  |  |
| --- | --- |
| Factor name | Mean (SD) |
| decision making | 4.65 (0.81) |
| training | 4.42 (0.91) |
| hotkeys | 4.28 (1.05) |
| resillience | 4.28 (0.83) |
| persistence | 4.21 (0.91) |
| multitasking | 4.16 (1.09) |
| selfconfidence | 4.14 (0.97) |
| strong will | 4.12 (1.03) |
| attention | 4.07 (1.03) |
| reaction time | 3.93 (1.10) |

Note: higher score means more important variable

Table 2

*Mean factors importance scores for success in MOBA games*

|  |  |
| --- | --- |
| Factor name | Mean (SD) |
| decision making | 4.55 (0.82) |
| teammates | 4.39 (0.88) |
| resillience | 4.33 (0.89) |
| strong will | 4.30 (0.92) |
| attention | 4.28 (0.77) |
| persistence | 4.27 (0.86) |
| selfconfidence | 4.12 (0.85) |
| intelligence | 4.02 (0.93) |
| training | 3.97 (1.07) |
| novelty seeking | 3.91 (0.95) |

Note: higher score means more important variable

Table 3

*Mean factors importance scores for success in FPS games*

|  |  |
| --- | --- |
| Factor name | Mean (SD) |
| decision making | 4.64 (0.69) |
| resillience | 4.43 (0.82) |
| teammates | 4.37 (0.84) |
| selfconfidence | 4.30 (0.83) |
| persistence | 4.28 (0.85) |
| strong will | 4.27 (0.89) |
| reaction time | 4.17 (0.88) |
| training | 4.15 (0.93) |
| attention | 4.14 (0.94) |
| spatial orientation | 4.06 (1.00) |

Note: higher score means more important variable

*Qualitative part*

Participants were also asked to propose variables they consider as most important for the success in esports. Items were formulated as follows: 1) „What makes a successful esports player? Name at least three abilities, traits, or skills. Start with the most important one.“ 2) „Which of those abilities, traits, and skills that you just mentioned are psychological? You can also name a new one. Start with the most important one.“ 3) „In addition to these abilities, traits, and skills, what are other factors that are important for being successful in esports? Start with the most important one.“ For suggested variables we have calculated weighted frequency based on the following rule: the first most important variable indicated by participants got 3 points, the second most important variable got 2 points and the third most important variable got 1 point. We have taken into account not only how often a specific variable was suggested but also whether it was suggested as the first in the order, second or third. Thus variables with highest scores were most frequently suggested by participants as the first or the second most important variables. First 10 most important variables were selected for the subsequent exploratory study.

The data and R code associated with this study can be found at https://osf.io/57dzm/

Table 4

*Weighted frequency of factors important for success in StarCraft 2*

|  |  |
| --- | --- |
| Factor name | Score |
| persistence | 42 |
| practice | 26 |
| intelligence | 19 |
| reaction time | 16 |
| mechanical skill | 15 |
| self-control (calm) | 11 |
| game related knowledge (game sense) | 10 |
| capacity to learn | 8 |
| intrinsic motivation | 7 |
| fast decision-making | 6 |
| Following factors with score smaller than 6: talent, resilience, high level of attention, multitasking, self-reflection, passion, adaptability, strategic thinking, patience, emotional intelligence, competitiveness ... | |

Table 5

*Weighted frequency of variables important for success in MOBA games*

|  |  |
| --- | --- |
| Factor name | Score |
| persistence | 36 |
| teamwork (communication) | 35 |
| self-control (calm) | 29 |
| mechanical skill | 25 |
| game related knowledge (game sense) | 24 |
| intelligence | 18 |
| patience | 15 |
| practice | 11 |
| fast decision-making | 10 |
| reaction time | 9 |
| Following factors with score smaller than 9: adaptability, high level of attention, self-reflection, capacity to learn, sociability, resilience, talent, emotional intelligence, humility, passion, strategic thinking ... | |

Table 6

*Weighted frequency of variables important for success in FPS games*

|  |  |
| --- | --- |
| Factor name | Score |
| mechanical skill | 236 |
| game related knowledge (game sense) | 167 |
| teamwork (communication) | 163 |
| persistence | 116 |
| resilience | 52 |
| capacity to learn | 42 |
| adaptability | 38 |
| intelligence | 37 |
| practice | 34 |
| high level of attention | 33 |
| Following factors with score smaller than 33: self-reflection, reaction time, talent, work ethic, intrinsic motivation, patience, fast decision-making, self-confidence, self-control (calm), positive mental attitude, good mental and physical health, passion... | |

**Appendix 2: Pilot 2**

Sample

Research sample consisted of 284 players (85.9% males) of esports game League of Legends with a mean age of 24.5 years and 290 players (95.2% males) of esports game Counter-Strike: Global Offensive) with a mean age of 24.87 years who self-identified as esports players. The data was collected via the Prolific platform (for all details, see supplementary materials) using a specific prescreening (responding yes to the item: ”Are you an esports player? (i.e., playing esports games on ranked levels)” and choosing a preferred game: ”What is the name of the esports game you play the most?”). Players were included in the final sample only if showed higher gaming activity at least a few games a month during the last 6 months (in case of CS:GO) or during the last gaming season (in case of LoL) measured with the item: „How actively did you play during the last 6 months?“ For sensitivity analysis we have also checked the results for players who played at least several games a week.

*Sample size justification*

Sample size was based on a-priori power analysis. Our SESOI r = 0.15 was based on systematic search of literature, summarized in Table 1 below and budget constraints. Our SESOI is significantly smaller than most of the published effects in Table 1 and according to Funder and Ozer (2019) consequential probably only in the long run and medium and potentially also consequential in the short run.

Apriori power analysis was calculated for power of an individual independent variable in the regression model. The required sample size of 230 participants was calculated considering the type of statistical analysis (hierarchical regression analysis and therefore t-tests family, Linear multiple regression: Fixed model, single regression coefficient in G\*Power (Faul et al, 2007) was chosen), inclusion of 31 predictors, α = .1, two tailed hypothesis, β = .90, and f2 = .0375 calculated from variance explained by predictor (.0225) and hypothesized residual variance (.6). Due to the exploratory nature of analysis stemming from this data collection, the seriousness of the Type I error was assumed to be the same as Type II error. Therefore alpha level was set to be 0.1 (for the rationale of adjusting error rates, see Lakens et al., 2018), the same as the power to be at least .9.

Measures

Dependent variables

Long-term success or performance in esports was based on a game skill ranking system measured with an item: a) “In the last 12 months, what was your highest rank in Counter-Strike: Global Offensive?” with response scale from Silver I to The Global Elite or “In the last season 11, what was your highest rank in League of Legends?” with the response scale from Iron IV to Challenger.

*Note*: In order to guarantee anonymity of respondents and to comply with the Prolific policy, it was not possible to gather objective data (e.g., steam links) associated with players accounts.

Independent variables – predictors

Predictors were selected based on the results of the pilot study (Appendix 1) and complemented with the variable concerning streaming (Matusi et al., 2020) identified during the systematic review of literature (Table 1).

Independent variables – predictors identical for both games

*Persistence* was measured using 5 items from the Short Grit Scale (Grit–S), (Duckworth & Quinn, 2009) consisting of all items from the Perseverance of Effort subscale and one from the consistency subscale, a better structure proposed by Lechner et al. (2019). Reliability represented by omega total coefficients were .79 (for LoL) and (.68 for CSGO).

*Intelligence* was measured using 6 items of the Short Form of the Hagen Matrices Test (Heydasch et al., 2020). Reliability represented by omega total coefficients were .78 (for LoL) and (.80 for CSGO).

*Resilience* was measured using 6 items of The Brief Resilience Scale (Smith et al., 2008). Reliability represented by omega total coefficients were .90 (for LoL) and (.86 for CSGO).

*Attention* was measured using the Visual search task and PsyToolkit software (Stoet, 2010; Stoet, 2017) and operationalized as the average response time across all correct trials (Treisman & Gelade, 1980).

*Strong will* was measured using 4 items of the Willpower: Action orientation subscale of the english version of the SSI-K3 scale (Kuhl & Fuhrmann, 2004). Reliability represented by omega total coefficients were .85 (for LoL) and (.88 for CSGO).

*Self-confidence* was measured using the single item measure of global self-esteem (Robins, Hendin, & Trzesniewski, 2001).

*Reaction time* was measured using the Deary-Liewald task and PsyToolkit software (Stoet, 2010; Stoet, 2017).

*Teamwork* as the ability to effectively cooperate and communicate with other team members was measured using the 8 items of the Teamwork Scale (Lower et al., 2015). Reliability represented by omega total coefficients were .82 (for LoL) and (.85 for CSGO).

*Speed of decision making* was measured using the Stop signal task and PsyToolkit software (Stoet, 2010; Stoet, 2017).

*Training* was measured using four items: 1) How many hours per day on average do you play GAME NAME? 2) Of all the time that you spend on esports, how many hours per day on average consist of *deliberate practice*, i.e. activities that need focused attention and aim at improving specific esports skills? 3) How many days per week do you play GAME NAME? 4) How long (in years) have you been playing GAME NAME?

*Physical training* was measured using the item “How much time per day (in minutes) on average do you do physical training (e.g., running, yoga, cross-fit)?”

*Customization* was measured using the item: “How much do you use technical arrangements that serve your esports performance such as customized hotkeys, mouse sensitivity, etc.?” on the 5-point rating scale ranging from very little to very much.

*Time for practice* was measured using the item “Do you have as much time available to play as you need?” on a 4-point Likert scale ranging from fully agree to fully disagree.

*Team membership* was measured using two questions: 1) “Do you have a player contract that provides you with financial or other benefits from an esports club, team, or sponsor?” 2) “Are you a member of an esports team or club without an official contract?”

*Streaming* was measured using the item: How often do you stream your games? (e.g., on Twitch or YouTube Gaming) on a 5-point rating scale ranging from never to very often.

*Team size* was measured using the question: “How many members does your team (club) have?”

Amount of *support* from team members, a coach or other people was measured using 3 items: 1) “In terms of your development as an esports player, how supportive is your coach or team?” 2) “In terms of your development as an esports player, how supportive are your friends?” 3) “In terms of your development as an esports player, how supportive is your family?” on a 5-point rating scale ranging from very little to very much.

*Marketability* represented by an image or brand of the player and its propagation (visibility) was measured using the item “How often do you work on your marketability? (e.g., building your brand, self-promotion activities)” using a 5-point rating scale ranging from never to very often.

*Equipment* was described as ownership of good hardware and peripherals and was measured using the item “How would you rate the quality of a hardware or specialized peripherals (e.g., keyboard, mousepad, headphones) with which you play?” using a 5-point rating scale ranging from very low quality to very high quality.

Self-perceived mechanical expertise defined as correct execution of specific actions with mouse or keyboard (e.g., micro skill, aim, skill shots, camera control, combo timing, spell order, etc.) was measured using the question “If you were to compare yourself with other players of the GAME NAME, how would you rate your mechanical skill (e.g., micro skill, aim, combo timing, spell order)?” with response options being percentiles (0th percentile (the worst player) - 100th percentile (the best player).).

*Self-perceived metagame expertise (game sense)* – represents a general understanding of the game or game mechanics in a broad sense. It includes a divergent set of abilities such as game awareness, game anticipation, knowledge of different strategies, movement patterns, or map knowledge. It was measured using the question “If you were to compare yourself with other players of the GAME NAME, how would you rate your game related knowledge - game sense (e.g., game awareness, game anticipation, map knowledge)?” with response option being percentiles (0th percentile (the worst player) - 100th percentile (the best player).).

Independent variables – Counter-Strike: Global Offensive

*Capacity to learn* (also called coachability) as the ability or willingness to learn or improve was measured using 4 items of The Motivation-to-Learn scale (Gorges et al., 2016). One of the respondents described it as „Being ready to improve everyday (look for new spots, new plays, new combos, new tactical grenades, aim training).“ Reliability represented by omega total coefficient was .86.

*Spatial orientation* was measured using the Mental Rotation Task and PsyToolkit software (Stoet, 2010; Stoet, 2017) and operationalized as the average response time across all correct trials ( Shephard & Metzler, 1971).

*Adaptability* was measured using 5 items from the Learning and 5 items from the Creativity subscale of the I-ADAPT-M (Ployhart & Bliese, 2006). Reliability represented by omega total coefficient was .84 (Learning) and .77 (Creativity).

Independent variables – League of Legends

*Self-control* was measured using 13 items of the Brief Self-Control Scale (Tangney et al., 2004). Reliability represented by omega total coefficient was .85.

*Patience* was measured using the single item presented in (Vischer et al., 2013).

All materials are available at: https://osf.io/zevng/

Outcome-neutral control

Subjective evaluation of skill was measured using the item: „If you were to compare yourself with all other players of the GAME NAME based on the number of wins or standing in the league (ranking), how would you rate your skill in the game?“with response options being percentiles (1st percentile (the worst player) - 100th percentile (the best player)). Subjective evaluation of skill was strongly associated (LoL: r = 0.71; CSGO: r = 0.73) with the dependent variable (skill rank).

*Data quality checks*

To control for careless responding and possible bots we have employed two specific items: 1) Bogus item: „I do not understand a word of English.“ to which respondent should respond using the option Not at all true, and 2) Instructed response item: „I can work all night long but ignore the previous part of the question and check Mostly like me.“ In addition to the above two items we have also used Mahalanobis distance statistic. Participants who failed in one of the two items and at the same time had Mahalanobis distance statistic higher than the alpha quantile of the chi-square distribution were omitted from analyses. From the LoL dataset, 22 participants (careless responders) were removed and 24 participants from the CSGO dataset.

Procedure

Measures were presented to respondents in following order: 1) demographics, 2) esports success/performance items, 3) team membership, team size, 4) training, active play (randomized), 5) customization, support (randomized), 6) mechanical expertise, metagame expertise (game sense), time availability, marketability, streaming, equipment (randomized), 7) intelligence, 8) all cognitive tasks (randomized), 9) all personality variables (randomized). Data collection was carried out using the Psytoolkit software (Stoet, 2010; Stoet, 2017).

Statistical analysis

The percentage of missing values for LoL was 0.5% and for CSGO was 0.8%, which were replaced with the chained random forests and the missRanger package (Mayer, 2021). None of the participants from the LoL dataset had more than 10% of missing data. From the CSGO dataset, three participants were removed having 11-13% of missing data.

The data and R code associated with this Pilot study can be found at: https://osf.io/zevng/.

Results

Results of OLS and robust regression analyses (High Breakdown-Point and High Efficiency robust estimates) are reported in tables (for each game title separately) provided as supplementary materials and available at: https://osf.io/qbd7x/

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**Appendix 3: Systematic database search**

To map out the available literature regarding the associations of various factors to esports performance, we carried out a database search using the search terms (“gaming” OR „esport\*“ OR „competitive\* play\*“) AND (“success“ OR “performance” OR “win\*” OR “rank\*” to the databases Scopus, Web Of Knowledge Core Collection, OSF Preprints, and ProQuest Dissertations/Theses. All abstracts were screened and 15 original empirical studies were found highly relevant for the present project.

The following search string were used:

Scopus:

TITLE-ABS-KEY((esports OR "competitive play" OR "competitive gaming") AND (success OR performance OR win\* OR rank\*)) AND LANGUAGE(english) AND DOCTYPE(ar OR cp OR ip)

Web Of Knowledge Core Collection:

TI=((esports OR "competitive play" OR "competitive gaming") AND (success OR performance OR win\* OR rank\*)) OR AB=((esports OR "competitive play" OR "competitive gaming") AND (success OR performance OR win\* OR rank\*)) AND LA=(English) AND DT=(Article OR

**Early Access OR Proceedings Paper**)

ProQuest Dissertations/Theses:

TI((esports OR "competitive play" OR "competitive gaming") AND (success OR performance OR win\* OR rank\*)) OR AB((esports OR "competitive play" OR "competitive gaming") AND (success OR performance OR win\* OR rank\*)) AND LA(English) AND DTYPE(Article OR **Early Access OR Proceedings Paper**)

OSF Preprints:

title:"esports" OR description:"esports" and lang:en

**Appendix 4:** **Rationales for each hypothesis**

SESOI for **CSGO** r = .3, SESOI for **LoL**: r = .2. Note that **H1** is defined by *pilot results* and *theory*, **H2** is defined by *pilot results* and *previous research*.

**H1a** (CSGO, LoL): *naive (any)* ***practice*** *will meaningfully predict long-term esports success.*

* Practice is known to improve almost any human skill. A player who has never played **CGSO** or **LoL** before will unlikely succeed as well as someone with a significant amount of practice hours in these esports.
* In both **CSGO** and **LoL**, in fact, long-term success (here: ranking) is partially *defined* by practice, as one can only climb in ranking by playing ranked matches that count toward practice hours in our measure. A high rank literally requires more play hours than low rank, albeit many play hours do not necessarily lead to a high rank.
* In previous research, Bonny et al. (2016) and Hulaj et al. (2020) (see Table 3) also found Dota 2 players with higher Matchmaking Ranking to have played more (r = .409; r = .59)
* Ericsson’s theory of deliberate practice also recognizes the value of non-deliberate practice.
* Pilot 2 shows significant zero-ordered effects of non-deliberate practice for both **CSGO** (*r* = 0.29) and **LoL** (*r* = .25), and the 95% confidence intervals of these effects exceed our respective SESOIs r = .3 [.16; .41] and r = .2 [.09; .41], indicating meaningful effects.

**H1b** (CSGO, LoL) ***deliberate practice*** *will meaningfully predict high long-term esports success*.

* This hypothesis derives specifically from Ericsson’s deliberate practice theory.
* A recent meta-analysis (Macnamara et al. 2018), which also involved games, found a significant positive effect for deliberate practise.
* Pilot 2, too, found evidence for a significant and meaningful deliberate practice effect in **LoL** (r = .25). The confidence interval clearly exceeded our SESOI r = .2 [.15; .37].
* Our Pilot 2 did not find evidence for a meaningfully significant deliberate practice effect in **CSGO** (r = .08). The confidence interval did not exceed our SESOI r = .3 [-.05; .21]. *Against this pilot evidence, we expect deliberate practice to have a meaningful effect also in* ***CSGO***. We believe our pilot measure was insufficient to fully capture the construct, and the effect will be more meaningful with the new measure.

**H2a** (CSGO, LoL) **reaction time** *meaningfully* predicts long-term esports success

* Pilot 2 found a small effect for **CSGO** (r = -.16), which did not exceed our SESOI r = .3. However, the confidence interval (-.34; .02) did not allow excluding the possibility of meaningful effect, for which we except a meaningful effect to occur at Stage 2.
* Pilot 2 found a small effect for **LoL** (r = -.14), which did not exceed our SESOI r = .2. However, the confidence interval (-.28; -.00) did not allow excluding the possibility of meaningful effect, for which we expect a meaningful effect to occur at Stage 2.

**H2b** (LoL) **teamwork** *meaningfully* predicts long-term esports success

* Pilot 2 found a small effect for **LoL** (r = .13), which did not exceed our SESOI r = .2. However, the confidence interval (.00; .25) did not allow excluding the possibility of meaningful effect, for which we expect a meaningful effect to occur at Stage 2.

**H2c** (LoL) **intelligence** *meaningfully* predicts long-term esports success

* Pilot 2 found a small effect for **LoL** (r = .12), which did not exceed our SESOI r = .2. However, the confidence interval (-.02; .25) did not allow excluding the possibility of meaningful effect, for which we expect a meaningful effect to occur at Stage 2.

**H2d** (LoL) **persistence** *meaningfully* predicts long-term esports success

* Pilot 2 found a small effect for **LoL** (r = .11), which did not exceed our SESOI r = .2. However, the confidence interval (-.05; .27) did not allow excluding the possibility of meaningful effect, for which we expect a meaningful effect to occur at Stage 2.

**H2e** (CSGO, LoL) **younger age** *meaningfully* predicts long-term esports success

* Although Bonny et al. (2016) did not find evidence for age effects in MOBA games, Kokkinakis et al. (2017) found younger age contributing to various genres (d = .4, d = .45, d = .38, d = .17).
* Pilot 2 found younger age having a small effect for **CSGO** (r = -.24), which did not exceed our SESOI r = .3. However, the confidence interval (-.37; -.12) did not allow excluding the possibility of meaningful effect, for which we expect a meaningful effect to occur at Stage 2. Pilot 2 shows younger age to have a significant and meaningful effect in **LoL** (*r* = .23 [-.37; -.09], indicating a clear meaningful effect at Stage 2.

**H2f** (CSGO) **attention** *meaningfully* predict long-term esports success

* Pilot 2 found a small effect for **CSGO** (r = -.17), which did not exceed our SESOI r = .3. However, the confidence interval (-.31; -.03) did not allow excluding the possibility of meaningful effect, for which we except a meaningful effect to occur at Stage 2.

**H2g** (LoL) **attention** does *not* meaningfully predict long-term esports success

* Pilot 2 found a null effect for **LoL** (r = .01), and the confidence interval (-.12; .09) did not allow expecting a meaningful effect (SESOI=.2). We expect a null effect to occur at Stage 2.

**H2h** (CSGO, LoL) **decision making speed** does *not* meaningfully predict long-term esports success

* Pilot 2 found a small effect for **CSGO** (r = .11), which did not exceed our SESOI r = .3. The confidence interval (-.01; .23) did not allow expecting any meaningful effect, for which we expect a null effect to occur at Stage 2.
* Pilot 2 found a small effect for **LoL** (r = .10), which did not exceed our SESOI r = .2. The confidence interval (.00; .20) did not allow expecting any meaningful effect, for which we expect a null effect to occur at Stage 2.

**H2i** (CSGO) **teamwork** does *not* meaningfully predict long-term esports success

* Pilot 2 found a null effect for **CSGO** (r = .02), and the confidence interval (-.13; .17) did not allow expecting a meaningful effect (SESOI=.3). We expect a null effect to occur at Stage 2.

**H2j** (CSGO) **intelligence** does *not* meaningfully predict long-term esports success

* Pilot 2 found a small effect for **CSGO** (r = .10), which did not exceed our SESOI r = .3. The confidence interval (-.02; .22) did not allow expecting any meaningful effect, for which we expect a null effect to occur at Stage 2.

**H2k** (CSGO) **persistence** does *not* meaningfully predict long-term esports success

* Pilot 2 found a null effect for **CSGO** (r = .02), and the confidence interval (-.14; .19) did not allow expecting a meaningful effect (SESOI=.3). We expect a null effect to occur at Stage 2.

**Appendix 5: The rationale for selecting SESOI r = 0.3 (CSGO) and SESOI r = 0.2 (LoL)**

As a real-life basis for all justifications, we use the unit of “one rank” as the smallest *visible indicator of change* (VIC) in one’s long-term esports success, i.e., VIC = 1 rank. Accordingly, our SESOI is defined by the *standardized effect that would lead to a change of rank* in real-life, assuming the ergodic premise is true (e.g., Molenaar 2004). The below justifications for **CSGO** are based on the regression coefficients from Pilot 2 (Table 3), which imply that r = 0.3 is widely sufficient across variables in terms of rank change. Because the **CSGO** ranking system is distributed across 18 ranks and the **LoL** ranking system is distributed across 27 ranks, approximately x1.5 effect (27/18=1.5) is required to climb a single rank in **CSGO** compared to **LoL**. Thus, we systematically use r = 0.2 as a SESOI for **LoL**, based on the below calculations for **CSGO**.

Based on Pilot 2 (Table 3) and specifically **CSGO**:

1. **Practice***.* With an effect r = 0.3, one practice hour/day would lead to a rank increase of 0.73. This is sufficiently close to a full rank to justify r = 0.3 as meaningful.
2. **Deliberate practice**. With an effect r = 0.3, one practice hour/day would lead to a rank increase of 0.78. This is sufficiently close to a full rank to justify r = 0.3 as meaningful.
3. **Attention**. With an effect r = 0.3, improvement of 1ms in the attention test would lead to a rank increase of 0.007. A full rank increase would thus require an improvement of 142ms, which is a similar difference to that between players and non-players of action games (140ms; Li et al., 2022) and players and non-players in general (196ms; Castel et al., 2015). It is also ~ ½ *SD* in our Pilot data. This is sufficient to justify r = 0.3 as meaningful.
4. **Decision-making**. With an effect r = 0.3, improvement of 1% in the go/no-go test score would lead to a rank increase of 0.08. A full rank increase would thus require 12% improvement, which is ~ ¾ *SD* in Pilot 2. This is sufficient to justify r = 0.3 as meaningful.
5. **Reaction time**. With an effect r = 0.3, test improvement of 1ms would lead to a rank increase of 0.04. Thus, 25ms improvement would lead to full rank increase. This corresponds to *SD* in professional esports players and ~ ½ *SD* in non-professional esports players (Bickmann et al., 2021). Our Pilot 2 coheres with the latter. This is sufficient to justify r = 0.3 as meaningful.
6. **Teamwork**. With an effect r = 0.3, improvement of 1 point in the teamwork test (scale 8–40) would lead to a rank increase of 0.3. Thus, ~3.5 points would lead to full rank increase. This corresponds to ~ ¾ *SD* in Pilot 2. This is sufficient to justify r = 0.3 as meaningful.
7. **Intelligence**. With an effect r = 0.3, a single point increase in our test (scale 0–6)—which equals to ~10 points in a standardized IQ score—would lead to a rank increase by 0.93. This is sufficiently close to a full rank to justify r = 0.3 as meaningful.
8. **Persistence**. With an effect r = 0.3, a single point increase in the test (scale 5–25) would lead to a rank increase by 0.6. A full rank increase would thus require 1.5 improvement in the test. This is sufficient to justify r = 0.3 as meaningful.
9. **Age**. With an effect r = 0.3, a single year less (youth) corresponds with 0.24 better rank. Thus, four years of younger age correspond with a full rank. This is sufficient to justify r = 0.3 as meaningful.

**References**

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**Appendix 6: Pilot 3 Development of Deliberate Esports Practice (DEP) Instrument**

Esports practice significantly differs from many other types of practice, for instance, because time spent playing is often both social and solitary at the same time. Moreover, esports games differ significantly, i.e., there is great variation between the (skill and other) demands set by esports games and the expertise that has developed in each game. The latter—universally developed level of expertise—is specifically important, as it is one of the requirements in deliberate practice theory for high-level (deliberate) practice to be possible. In other words, deliberate practice *might* *not even be possible* in some types of esports, which still lack the field-specific professional knowledge that is used to produce efficient deliberate practice activities. It is also critical note that the differences between “naive”, “purposeful”, and “deliberate” play (as the three classes of practice identified by Ericsson & Pool, 2016) can be difficult to assess in esports contexts, which are designed as commercial entertainment products. Therefore, instead of applying old deliberate practice instruments that have been developed for domains such as music and sports, we developed a new esports-specific instrument to carry out reliable analyses.

To develop a Deliberate Esports Practice (DEP) instrument, we crafted a research design based on new qualitative data from high-ranked players in four different esports games: CSGO, LoL, Fortnite, and Hearthstone. The ranking systems of all four titles are described as follows.

* Ranks in CSGO are based on number of wins and losses in competitive matches, specifically on modified Glicko-2 ([https://glicko2.js.org](https://glicko2.js.org/) ).
* Ranks in LoL are based on Matchmaking rating (MMR), in which players earn or lose League Points by winning and losing. MMR ensures that players at every rank play against roughly equally strong opponents, thus higher rank means that the player achieved more wins against more skilled opponents.
* Ranking in Fortnite operates on Hype points that players earn by killing more opponents and the duration they can stay alive in each match. For each match, players need to pay some amount of Hype points called Bus fare, which leads to a loss of Hype points in the situation of bad performance (e.g. small amount of kills).
* Ranking in Hearthstone is divided into three separate ranked ladders: Standard, Wild, and Classic. Each ladder consists of five leagues: Bronze, Silver, Gold, Platinum, and Diamond. Each league, at the same time, consists of 10 ranks (1–10). In addition to the above, there is a separate “Legend“ division reserved for the top players.

Method

Using the services of Prolific, we surveyed 40 high-ranked players with an open question about practice from four different esports games (10 players of Counter-Strike: Global Offensive (at least on the level of Master Guardian I), 10 players of Fortnite (at least on the level of Contender I), 10 players of Hearthstone (at least on the level of Platinum), and 10 players of League of Legends (at least on the level of Diamond)). The specific survey question was: *What are the different types of practice/training (or other activities) that you have done to advance your 'in-game' performance in esports? (List as many as you can in the order of importance).* Additionally, we directly contacted four professional League of Legends coaches/players (two European and two Korean) and interviewed them about the same question. Two authors (YJ, VMK) inductively coded the data (*N* = 44) to identify distinct types of esports practice, and these types were then collectively clustered in a mutual meeting with all authors into eight deliberate practice types. The data were then re-coded deductively with the eight clusters by the first author (MM). For the data, see: https://osf.io/kcaes/.

Results

Table 1

*Responses and identified types of practice*

|  |  |  |
| --- | --- | --- |
| Response | INDUCTIVE | DEDUCTIVE |
| Counter-Strike: Global Offensive |  |  |
| - aimlab~~- better PC components | aim practice | playing alone |
| Training on Aim\_BotZ~~FFA~~Retakes~~MM~~ | 1 aim practice  2 specific map play | 1,2 playing alone |
| Time trails ~~bot games~~callout practices~~team practice~~general gameplay against other guardian levels | 1 specific map play  2 team practice  3 increasing game knowledge | 1 playing alone  2 playing with a team  3 strategic learning alone |
| -I used to play competitively when I was younger so that carries the most weight.~~-When you lose a 1v1 or any situation, going through quickly what you might have done differently with the information you had, instead of blaming luck or enemy.~~-focusing on Teamwork/map awareness, and trying to get better at it+ communication. Alot of newer players can shoot, but don't understand what's going on around the map or communicate well.~~-warmup in one of those aim maps vs bots.~~-Taking a break when you feel tilted/too tires to focus. | 1 aim practice  2 team communication | 1 playing alone  2 strategic learning with others |
| Sniper accuracy training on special maps~~~~Training matches with bots sam vs 5~~~~Training with colleagues | 1 aim practice  2 specific map play | 1,2 playing alone |
| 1000 kills on aimbotz~~30 min on ffa server~~review some pro demos | 1 aim practice  2 watching others to play | 1 playing alone  2 strategic learning alone |
| - aim training maps~~- deathmatch~~- grenade practice | 1 aim practice  2 grenade practice | 1,2 playing alone |
| -aimmap~~-deathmatch~~-arena servers~~-playing faceits~~-aimlab | aim practice | playing alone |
| I usually play deathmatch before every comp for about 20 minutes. Sometimes I pratice my aim in AimLab. I watch map guide videos to learn the tactics and some tricks in specific maps.~~ | 1 routine play  2 aim practice  3 watching others to play  4 specific map play | 1 routinely playing the game  2,4 playing alone  3 strategic learning alone |
| Fortnite | INDUCTIVE | DEDUCTIVE |
| watching top players youtube challenge~~developing a routine~~improving reaction times ~~shooting practices~~paying for toturials | 1 specific map play  2 watching others to play  3 aim practice  4 coached practice | 1,3 playing alone  2 strategic learning alone  4 strategic learning with others |
| I mainly play team rumble or duo with my brother. ~~Always trying to complete the weekly objective.~~Trying to get better at my accuracy. | aim practice | playing alone |
| I practise in aim trainer. I tweak my mouse sensitivity. In my room is calm. I try to practise with better players. | aim practice | playing alone |
| jogging, walking, breathing exercises | 1 physical exercise  2 breathing exercise | 1 physical practice  2 mental pracice |
| watching videos on youtube and live videos of games~~joining esport clubs~~doing research for best strategies in gaming | watching others to play  club membership | strategic learning alone  strategic learning with others |
| Maximizing speed in preparing for battle.~~Accuracy training in aiming. Trying to get to the best spot as soon as possible. | aim practice | playing alone |
| I have watched youtube videos of people ranked higher than me to know what to do in certain situations. Also, I tend to search for specific problems I tend to have when playing. | 1 watching others to play  2 increasing game knowledge | 1,2 strategic learning alone |
| Practice shooting during the training portion of the game~~Shooting at wildlife such as the wolves & boars that appear in the game~~Completing missions for the season | aim practice | playing alone |
| play with better players,~~watch youtube videos to learn~~play with friends | 1 watching others to play  2 team play | 1 strategic learning alone  2 playing with a team |
| - Carry out a lot of training in front of the computer in terms of speed in maneuvering keyboard/joystick;~~- Study the game in all its features to get the best out of it and know how to govern it~~- Studying the game mode of my opponents, in case I don't have to play against the computer but against real users~~- Learning tricks from other users via live session | 1 improving mechanical expertise  2 increasing game knowledge  3 watching others to play | 1 playing alone  2,3 strategic learning alone |
| Hearthstone | INDUCTIVE | DEDUCTIVE |
| 1. I focus on the current meta, maybe for one or two decks. I set up one or two decks according to the meta and grind them out until I really get the hang of them.~~~~2. I watch lots of tip videos on youtube, and HS streams~~~~3. I have friends who have a higher rank than me. I play against some of them at least once a day.~~~~4. I review my games, especially the ones I lost to see where I could improve~~~~5. When I slump I take a break for a couple of days from ranked, and continue watching videos and streams~~~~6. I try to play as accurate as possible | 1 grinding, repetition play  2 videos  3 skrimming, social practice  4 self-reflection  5 rest  6 optimization | 1,6 playing alone  2 strategic learning alone  3 playing with a team  4,5 mental practice /relaxing activities outside the game |
| Watching tips and other players on stream / youtube.~~Dedicating time to approach things in a different way.~~Reviewing competition play backs from previous games.~~Trying something new each time.~~Play against players of different levels, understand thought patterns etc. | 1.1 videos  1.2 tips (“pseudo- coaching”)  2 experimentation (x2)  3 self-reflection  4 reading other players; social practice | 1 strategic learning alone  2 playing alone  3 mental practice  4 playing with a team |
| Play more and more to improve | grind, mindless | playing alone |
| Test new strategies~~Watch others play~~Play other card games | 1 experimentation  2 videos  3 play other games | 1 playing alone  2 strategic learning alone  3 playing with a team |
| Know about your opponent's hand~~~~Know about your opponent's deck~~~~Know about your deck~~~~Knowabout how card effects resolve | 1.1 reading the game  1.2 reading opponent  1.3 knowing oneself  2 game knowledge | 1,2 strategic learning alone |
| 1. Compete in a group of players with a similar level to me.~~2. Learn and predict what my opponents might do and counter attack or block.~~3. Record and rewatch my matches to analyse how I performed.~~4. Watch online competitive matches from high-level players, and learn how they play.~~5. Participate in tournaments to see how I fair against others, network and build relationships. | 1 social learning  2 reading opponent  3 self-reflection  4.1 “pseudo-coaching”  4.2 learning from pros  5 compete, learning by failing  6 build social network | 1,5 playing with a team  2 strategic learning alone  3 mental practice  4 strategic learning alone  6 playing with others |
| Scouting, learning from my experience, setting objectives, communication with teammates, practising skills. | 1 scouting (learning about other players)  2 self-reflection  3 goal setting  4 communication  5 focused repetition | 1 strategic learning alone  2,3 mental practice  4 strategic learning with others  5 playing alone |
| League of Legends (Prolific) | INDUCTIVE | DEDUCTIVE |
| Analyzing games that I have played in order to find mistakes and improve my gameplay on the macro and micro basis. ~~~~Taking screen-breaks of at least 5 minutes after every game, especially after losses. ~~~~Playing the first game of the day on an alt-account to build up focus and routine, before switching to my main account. ~~~~ | watching others to play  screen breaks | strategic learning alone  mental practice |
| I'm watching coaching videos on YouTube sometimes~~I watch proplay, but i'm doing that really rarely~~And sometimes when i'm losing free win. I watch replay~~to look what i did wrong | watching others to play | strategic learning alone |
| Watching videos online and reading about different strategies. | 1 watching others to play  2 increasing game knowledge | 1,2 strategic learning alone |
| Being as fit as possible for improvement of mental health and avoiding muscle/bone issues, especially for the back and wrists~~Theory crafting~~Watching pro players playing live~~Rewatching the games played to see the mistakes commited | 1 physical exercise  2 increasing game knowledge  3 watching others to play | 1 physical practice  2,3 strategic learning alone |
| Can't say that I do any kind of specific training. I try my best to not be toxic towards the other players, play just a few characters that I know well and after a lost game I just think, what I could have done better (even if it was absolutely not my fault). | self-reflection | strategic learning alone |
| just playing the game~~training mode in counter strike~~training mode LOL~~sleep~~ | routine play  specific map play | routine play  playing alone |
| -Observe the techniques and strategies of higher ranked players. try to learn and imitate.~~-Play in a quiet environment. This way you can be fully concentrated.~~-Analyze my previously played games, mark my mistakes and correct them.~~-Get good friends/rivals to practice with, get different opinions about your mistakes and how to improve.~~-Get friends/rivals of a similar or higher rank to practice with, get different opinions about your mistakes and how to improve.~~-Have a schedule and mark how much time you dedicate to practice and how much time you dedicate to play.~~-Choose a hero that works for you, analyze his strengths, weaknesses, role and how he synergizes with the other hero in your team.~~-Have good hardware for competitive gaming, you don't need the best but a mouse with high sensitivity and response time, a good monitor and a mechanical keyboard can make the difference. | 1 watching others to play  2 team play  3 team discussions  4 increasing game knowledge | 1,4 strategic learning alone  2 playing with a team  3 strategic learning with others |
| reflex training, play more games | mechanical skill training  routine play | playing alone  routine play |
| Most of the time is just watch guides, stay a lot of hours in practice tool testing out the stuff I learned, then go to the real games and see what I'm worth | watching others to play | strategic learning alone |
| Watch video, play different characters multiple times, read forums | 1 watching others to play  2 increasing game knowledge | 1,2 strategic learning alone |
| League of Legends (Pro players) | INDUCTIVE | DEDUCTIVE |
| - Scrimming 2-3 blocks of scrims 4-5 days a week - Playing eye test and memory games before game days - Meditating before games start / doing breathing exercises on game days - Doing phsyical exercise 2-3 times a week before or after scrims - Having nutritionists plan diets / deliver healthy meals for good energy during scrims, eating alot of carbs or unhealthy meals causes energy crashes after game 2-3 of scrims and it becomes unproductive - Lots of meetings with players before and after scrims to figure out team direction | 1 team play  2 eye training  3 cognitive skills training  4 meditation  5 breathing exercise  6 physical exercise  7 team discussions | 1 playing with a team  2,6 physical practice  3,4,5 mental practice  7 strategic learning with others |
| I exercise around 3,4 times a week, especially like eto do it on game day 2,3 hours before the match so I raise my blood flow and awareness, I also like to play guitar in the morning for atleast 15 min to warm up my fingers and brain before practice | 1 physical exercise | physical practice |
| Literally grinded the game for +16 hrs a day (the best way to understand the game)  Watched streams/videos of same role(position) and tried to emulate the different playstyles | watching others to play | strategic learning alone |
| - “First, playing the game a lot. I aimed to get better with experience and also to expand my understanding of the game”  - “:I also read/watched a lot of other people’s written tips, community discussions, and what they experienced in the game. Including the videos, (highlights, informational, fun clips) as an indirect experience, I could not experience myself.”  - “In team training, what most helped me was the discussion with coaches and teammates.”  - “I also warmed up before single play with bots, focusing on cs”  - “I also wrote a game diary(?), right after solo rank or scrims. Like how I played on the lane and the result was such such. Where it became challenging. On things I tried, what worked or what didn’t. Guess it wasn’t really a diary, but more like a short sentence or two.”  - (my f/u question: can you elaborate on what you mean by discussion in team training? ) “It was like an opinion exchange, like how about we try this? I would say, ‘Theory Crafting’”(his own English word) | 1 routine play  2 watching others to play  3 increasing game knowledge  4 team play  5 team discussions | 1 routine play  2, 3 strategic learning alone  4 playing with a team  5 strategic learning with others |

Summary of the coach interview:

* In his mental coach view, training/practice could be broadly divided into mental training (led by mental coach) and actual training (led by regular coach). Actual training is also divided into strategy/tactics and game skill.
* Aside from coaches, the role of team manager/lead coach is usually focused on understanding individual characteristics of players and managing team dynamics (which often is ruined by a really good player who is not good at social skills, attitudes, tenacity etc.)

Conclusions

Based on the data and analysis, we have identified eight distinct practice types:

1. routinely playing the game (ranked mode, non-ranked mode, etc.)
2. mental practice outside the game (meditation, breathing exercise, etc.)
3. physical practice outside the game (gym, running, etc.)
4. relaxing activities outside the game (watching streams, talking to other players, etc.)
5. strategic or tactical learning alone (focused learning from guides, videos, etc.). This does not include playing.
6. strategic or tactical learning with others (having team discussions, being coached, etc.). This does not include playing.
7. playing the game alone with a specific goal to improve chosen esports-specific skills (aim or last-hit practice, playing with strangers to learn distinct scenarios/match-ups, etc.)
8. playing the game with experts, team, or other people with a specific goal to improve esports-specific skills (playing in communication with own team members, under a coach, etc.)

In the light of deliberate practice theory, we regard the first four practice types as “naïve” practice. Because the conceptual difference between “purposeful” and “deliberate” practice is defined by the degree to which the activity is *properly informed* (by high-level expert knowledge that has accumulated in the field, i.e. a specific esports game), it remains difficult to meaningfully distinguish these concepts in a self-report measure. Therefore, we choose to include all the latter four practice activities for measuring the *deliberate practice* construct in esports. In the future, new scale development studies could pursue improved measures, in case theorists consider it critical to separate between purposeful and deliberate practice across esports types that may have highly developed expertise knowledge. The items that we use for measurement are presented below.

**During the years of playing Counter-Strike: Global Offensive and/or similar games, how many *hours per week* on average would you estimate having spent on the following practice activities?**

*The first four activities can be described as practice that* ***require*** *focused attention and directly aim at improving esports-specific skills.*

- Strategic or tactical learning alone (focused learning from guides, videos, etc.)? This does **not** include playing.

- Strategic or tactical learning with others (having team discussions, being coached, etc.)? This does **not** include playing.

- Playing the game alone with a specific goal to improve chosen esports-specific skills (aim or last-hit practice, playing with strangers to learn distinct scenarios/match-ups, etc.)?

- Playing the game with experts, team, or other people with a specific goal to improve esports-specific skills (playing in communication with own team members, under a coach, etc.)?

**During the years of playing Counter-Strike: Global Offensive and/or similar games, how many *hours per week* on average would you estimate having spent on the following practice activities?**

*The next four activities can be described as practice that does* ***not directly*** *aim at improving esports-specific gaming skills. Do not report here any practice that you already reported in the previous four practice types.*

- Routinely playing the game (ranked mode, non-ranked mode, etc.)

- Physical practice outside the game (gym, running, etc.)?

- Mental practice outside the game (meditation, breathing exercise, etc.)?

- Relaxing activities outside the game (watching streams, discussing the game, etc.)

We then conducted a small pilot with n=31 LoL and n=34 CSGO players, using Prolific, with a focus on the comprehension of these practice items and their operationalization. We asked feedback such as "Briefly explain why you chose this number.” All survey items and data are available at: <https://osf.io/2g5ys/>

**Pilot 4 Checking comprehensability of the Deliberate Esports Practice (DEP) items**

Reliability for both samples: McDonald's Omega for practice = .868, McDonald's Omega for deliberate practice = .785

Reliability for LoL: McDonald's Omega for practice = .804, McDonald's Omega for deliberate practice = .670

Reliability for CSGO: McDonald's Omega for practice = .895, McDonald's Omega for deliberate practice = .863

Three respondents reported a problem recalling the highest rank LoL (out of 31), and five players in CSGO (out of 34). In the latter, four reports concerned their inactivity as players over the past year, which led us include oversampling in our final design and remove participants who have not played recently. The following issues were reported: difference between learning alone and learning with others; difference between routinely playing the game and playing with coaches.../alone.

**Table2**

*Correlations between rank and practice*

|  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- |
|  | League of Legends | | | Counter-Strike: Global Offensive | | |
|  | practice (4 items)  Pearson's r *(p-value*) | practice (1 item\*)  Pearson's r *(p-value*) | deliberate practice  Pearson's r *(p-value*) | practice (4 items)  Pearson's r *(p-value*) | practice (1 item\*)  Pearson's r *(p-value*) | deliberate practice  Pearson's r *(p-value*) |
| highest rank in 12 months | .470 (.009) | .418 (.021) | .268 (.153) | .378 (.048) | .264 (.175) | .189 (.334) |
| highest ever rank | .399 (.029) | .396 (.030) | .144 (.449) | .370 (.053) | .272 (.162) | .326 (.090) |
|  |  |  |  |  |  |  |
|  | practice (4 items) multiplied by career length  Pearson's r *(p-value*) | practice (1 item\*) multiplied by career length  Pearson's r *(p-value*) | deliberate practice multiplied by career length  Pearson's r *(p-value*) | practice (4 items) multiplied by career length  Pearson's r *(p-value*) | practice (1 item\*) multiplied by career length  Pearson's r *(p-value*) | deliberate practice multiplied by career length  Pearson's r *(p-value*) |
| highest rank in 12 months | .480 (.007) | .499 (.005) | .313 (.092) | .222 (.257) | .107 (.587) | .170 (.386) |
| highest ever rank | .400 (.028) | .448 (.013) | .184 (.330) | .210 (.284) | .082 (.680) | .252 (.195) |

*Note*: 3 participants reporting spending more than 100 hours per week on practice and deliberate practice were removed from the analyses. \* = only gaming hours.

As a consequence of the feedback, we reorganized the items into a clearer structure and did small modifications in how they were expressed. Because the modifications were relatively small and concerned reorganization, we decided not to carry out a fifth pilot. The final measure is below.

**During the past 12 months of playing GAME NAME, how many *hours per week* did you spend on the following activities?**

The first two activities require focused attention and *directly* aim at improving **esports rank/skills**.

* Learning *alone* (from guides, videos, streams, replays, etc.)? This does **not** include playing.
* Learning *with others* (getting feedback from teammates or coaches, team discussions, etc.)? This does **not** include playing.

The next three activities do *not directly* aim at improving **esports rank/skills**.

* Physical practice (gym, running, etc.)?
* Mental practice that is **not** playing (meditation, breathing exercise, etc.)?
* Relaxing esports activities that are **not** playing (watching streams, discussing the game, etc.)

The last activities specifically concern **playing** esports game(s).

The first two require focused attention and *directly* aim at improving **esports rank/skills**.

* Playing with *coaches, team*, or other experts (with tactical communication, reflection, etc.)
* Playing the game *alone* (practicing aim or last-hit, game scenarios/matchups, etc.)?

The final activity does *not directly* aim at improving **esports rank/skills**.

* Routinely playing the game (ranked mode, non-ranked mode, with or without friends, etc.). Please, exclude hours spending on previous two activities.

Game-specific career length (= number of years) will be used as a multiplier for the above two practice constructs: “How many years have you played [GAME NAME] **actively,** i.e. with higher or similar intensity as during the past 12 months?”

**References**

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1. Description and sample task of our cognitive measures (Visual search task, Stop signal task, and Deary-Liewald task): https://www.psytoolkit.org/experiment-library/ [↑](#footnote-ref-2)