**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 1, 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) | NA | 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 group |
| Kokkinakis et al. (2017) | 1669 Destiny players | matchmaking ranking | age | d = .45 | 22–27 year old group had better performance than 28+years 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 group |
| Kokkinakis et al. (2017) | 17861 LoL players | matchmaking ranking | age | d = .17 | 22–27 year old group had better performance than 28+years group |
| Mora-Cantallops & Sicilia (2018) | 547 LoL players | player’s rank | competence | NA | players with higher rank felt more competent (at the game) |
| Mora-Cantallops & Sicilia (2018) | 547 LoL players | player’s rank | presence (immersion) | NA | players with lower rank felt higher physical, emotional, and narrative immersion (feelings of being in the game) |
| 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 played more Dota games |
| Hulaj et al. (2020) | 329 Dota 2 players | matchmaking ranking | motivation: integrated regulation | r = .18 | players with higher matchmaking ranking had 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 perceived relationships in the game as more important |
| Li et al. (2020) | 70 LoL players | LoL ranking system (Iron-Challenger) | cognitive flexibility (task-switching costs) | d = −.49; d = −.57; d = −.77 | players in Bronze:Diamond group had higher task-switching costs and more errors compared to Master and over group |
| Matuszewski et al. (2020) | 206 LoL players | LoL ranking system (Bronze-Challenger) | extraversion | ηp2 = .03 | players from the three lowest (Bronze, Silver, and Gold) ranks had lower scores than players from thethree highest (Platinum, Diamond, and Master) divisions |
| Matuszewski et al. (2020) | 206 LoL players | LoL ranking system (Bronze-Challenger) | agreeableness | ηp2 = .02 | players from the three lowest (Bronze, Silver, and Gold) ranks had lower scores than players of thethree highest (Platinum, Diamond, and Master) divisions |
| Matuszewski et al. (2020) | 206 LoL players | LoL ranking system (Bronze-Challenger) | openness | ηp2 = .03 | players of the the three lowest (Bronze, Silver, and Gold) ranks had higher scores than players of thethree highest (Platinum, Diamond, and Master) divisions |
| Trotter et al. (2021) | 1440 adult esports players (mostly playing Overwatch, LoL, CSGO, Rocket League, and Dota) | four rank categories based on percentages | social support | ηp2 = .02 | players in the top 10% skill group received moreesteem, emotional, informational, and tangible support |
| Trotter et al. (2021) | 1440 adult esports players (mostly playing Overwatch, LoL, CSGO, Rocket League, and Dota) | four rank categories based on percentages | self-regulation | ηp2 = .21 | players in the top 10% skill group reported higher scores for triggering, informational input, searching, planning, and assessing |
| Trotter et al. (2021) | 1440 adult esports players (mostly playing Overwatch, LoL, CSGO, Rocket League, and Dota) | four rank categories based on percentages | psychological skill use | ηp2 = .37 | players in the top 10% skill group reported higher scores for self-talk, automaticity, goal-setting, imagery, and activation |
| Toth et al. (2021) | 39 CSGO 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) |

Notes: CSGO = Counter-Strike: Global Offensive, LoL = League of Legends

 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.

**Pilot studies**

 In order to formulate and test informative hypotheses, we carried out four pilot studies based on the literature.

* Pilot 1 was carried out to (dis)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 21.6 from multiple esports titles and asked them to rate the importance of 25 variables extracted from the existing literature. The five most important variables in MOBA games (League of Legends (LoL) 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 (CSGO), 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 detailed results, see Appendix 2 (https://osf.io/87bmg). R script and data are available at 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 CSGO and *N2* = 284 from LoL, 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 (with the same SESOI for CSGO and LoL being r = .15 for point estimates) within the models differed between the two titles. Esports success in CSGO was predicted by practice, age, attention, and reaction time and in LoL by deliberate practice, practice, and age listed from strongest to weakest predictor. Detailed description, descriptive statistics, and summarized results of hierarchical regression analyses are presented in Appendix 3 (<https://osf.io/qbd7x/>). R scripts and data are available at https://osf.io/qbd7x/.
* Pilot 3 and Pilot 4 were carried out to develop and test a new instrument intended to measure practice and deliberate practice in esports. We surveyed 40 high-ranked players from four different esports games (10 players of CSGO, 10 players of Fortnite, 10 players of Hearthstone, and 12 players and 2 coaches of LoL) with an open-ended question: 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). Two authors inductively coded the data to identify distinct types of esports practice, and these types were then collectively clustered into eight deliberate practice types. Items of the instrument are presented in Table 2. The comprehensibility of the new instrument (operationalization of the eight types) was tested on 65 players of CSGO and LoL. For detailed results, see Appendix 6 (<https://osf.io/2nrqb>). Data are available at <https://osf.io/kcaes/> (Pilot 3) and <https://osf.io/2g5ys/> (Pilot 4).

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**Present study**

 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 (LoL), Counter-Strike: Global Offensive (CSGO), 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, Appendix 2, https://osf.io/bwk69). 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.

**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 LoL (Sample 1), CSGO (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 our 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 our 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.

***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. LoL, CSGO, 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 LoL 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 LoL, with the following two caveats: the information load is not as high as in LoL (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 CSGO, yet teamwork tends to operate differently and there is an increased element of uncertainty across skill domains due to variation in starting location.

**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 LoL, from Silver I to Global Elite (18 different ranks) for CSGO, 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 two items (NP4-NP5) but for exploratory analyses with all five naive practice items (NP1—NP5). 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). 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, “naive practice” and “deliberate practice” are calculated by multiplying respective practice time with game-specific career length.

1. **Naive practice** and
2. **deliberate practice** will be measured with a new instrument, presented in Table 2.

**Table 2**

*Deliberate Esports Practice (DEP)*

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| **Deliberate Esports Practice** (DEP) |
| Item description | Item content |
| **Instruction:** 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**. |
| Deliberate Practice (DP1) | Learning *alone* (from guides, videos, streams, replays, etc.)? This does **not** include playing. |
| Deliberate Practice (DP2) | Learning *with others* (getting feedback from teammates or coaches, team discussions, etc.)? This does **not** include playing. |
|  |  |
| **Instruction:** The next three activities do *not directly* aim at improving **esports rank/skills**. |
| Naive Practice (NP1) | Physical practice (gym, running, etc.)? |
| Naive Practice (NP2) | Mental practice that is **not** playing (meditation, breathing exercise, etc.)? |
| Naive Practice (NP3) | Relaxing esports activities that are **not** playing (watching streams, discussing the game, etc.). |
|  |  |
| **Instruction:** The last activities specifically concern *playing* esports game(s). The first two require *focused attention* and *directly* aim at improving **esports rank/skills**. |
| Deliberate Practice (DP3) | Playing with *coaches*, *team*, or *other experts* (with tactical communication, reflection, etc.). |
| Deliberate Practice (DP4) | Playing the game *alone* (practicing aim or last-hit, game scenarios/matchups, etc.)? |
|  |  |
| **Instruction:** The final two activities do *not directly*. Please do not include gaming hours that you have already reported in previous activities. |
| Naive Practice (NP4) | Routinely playing the game in ranked mode (alone or with others). |
| ‍Naive Practice (NP5) | Routinely playing the game in non-ranked mode (alone or with others). |

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) available on the 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 available on the 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 available on the 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, age, persistence, and intelligence

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

The effects of persistence and intelligence, which are in both equations, need to meet the SESOI in each model to corroborate the 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 the 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 LoL respondents, ranking is measured by icons instead of a text (see https://osf.io/3atnf/). For the players of CSGO and Fortnite, identical items measuring ranking with response options presented backwards will be used.

***Data quality checks***

 To account for 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 at least 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.

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)