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Personality Psychology

Psychological Predictors of Long-term Esports Success: A Registered Report

Marcel Martončik[1,2,a], Veli-Matti Karhulahti[2], Yaewon Jin[2,3,4], Matúš Adamkovič[1,2,5]

[1] Institute of Social Sciences, Centre of Social and Psychological Sciences SAS, Slovakia, [2] Department of Music, Art and Culture Studies, Faculty of Humanities and Social Sciences, University of Jyväskylä, Finland, [3] The Game-n-Science Institute, South Korea, [4] Graduate School of Communication & Arts, Yonsei University, South Korea, [5] Faculty of Education, Charles University, Czechia

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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 was to test whether deliberate practice theory, which has successfully been applied to other sports earlier, can predict high esports performance with other psychologically relevant variables. The study was carried out with participants from Counter-Strike: Global Offensive (N = 186) and League of Legends (N = 411). In both esports, we found evidence for deliberate practice not having a meaningful effect on performance (null: r > .3 in Counter-Strike: Global Offensive and r > .2 in League of Legends, observed: .02 in Counter-Strike: Global Offensive and -.01 in League of Legends). On the other hand, the results confirmed younger age predicting better performance (-.33 and -.22, respectively). Additionally, we were able to confirm two game-specific findings: attention (-.30, Counter-Strike: Global Offensive) and non-deliberate practice hours (.26, League of Legends) meaningfully predicted performance in one but not both esports. The effects of all other variables—including intelligence, reaction time, and persistence—were confirmed to be null or inconclusive in both esports. We discuss the results against game design and hypothesize esports-specific information density as a potential explanation to differences in performance prediction. The findings can be useful for esports teams, coaches, and all individuals pursuing success in esports.

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".

a Corresponding author: Marcel Martončik, Institute of Social Sciences CSPS SAS, Karpatská 1337/5, Košice, 040 01, Slovakia. Email: martoncik@protonmail.ch

MM and VMK are joint first authors of this study

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 (Macnamara et al., 2016), for 24% of the variance in habitual gaming performance (Macnamara et 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 = .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/fxhjd), the results of which are summarized in Table 1.

Additionally, we found four qualitative studies that reported interviews with high-level esports players. For Overwatch, the relevance of game sense and mechanics were

Table 1. Relationships between long-term esports success and environmental, psychological, and other factors

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

Study	Study sample	Esports performance variable	Correlate	Effect size	Notes
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	ηp^2 = .03	players from the three lowest (Bronze, Silver, and Gold) ranks had lower scores than players from the three highest (Platinum, Diamond, and Master) divisions
Matuszewski et al. (2020)	206 LoL players	LoL ranking system (Bronze-Challenger)	agreeableness	ηp^2 = .02	players from the three lowest (Bronze, Silver, and Gold) ranks had lower scores than players of the three highest (Platinum, Diamond, and Master) divisions
Matuszewski et al. (2020)	206 LoL players	LoL ranking system (Bronze-Challenger)	openness	ηp^2 = .03	players of the the three lowest (Bronze, Silver, and Gold) ranks had higher scores than players of the three 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	ηp^2 = .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	ηp^2 = .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	ηp^2 = .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

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, persistence, 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, strong will, 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/fxhjd). 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 (N_1 = 290 from CSGO and N_2 = 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/fxhjd). 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/fxhjd). Data are available at https://osf.io/kcaes/ (Pilot 3) and https://osf.io/2g5ys/ (Pilot 4).

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/fxhjd). By *null* we mean the absence of such meaningful effect. If we fail to find evidence for both meaningful and null effects, we infer *inconclusiveness*. For a detailed rationale of each hypothesis, we refer to Appendix 4 (https://osf.io/fxhjd).

- **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 Faculty of Arts, University of Presov.

Participants

Survey data were collected via the Prolific platform. The samples consisted 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 were measured by the item: "What is the name of the esports game you play the most?" Detailed description of the samples are presented in Table 3. Our surveys were distributed in English, but we have not controlled the nationality or language skills of our participants. We generally relied on the data quality of Prolific, but see our quality checks below.

The sample size was 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/fxhjd). Required sample size (N_1 = 143 in CSGO and N_2 = 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 f^2 =.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 oversampled 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 have oversampled all samples by additional 10%, thus having the final samples of N_1 = 186 and N_2 = 411. We have used the same sample size of N_3 = 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 mid-2023, there are approximately 165 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 was 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 have also applied 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 was measured by a new instrument specifically developed for this study after the piloting phase (Pilot 3 and Appendix 6, and Pilot 4 for clarity check, https://osf.io/fxhjd). The instrument involves items representing "naive practice", "purposeful practice", and "deliberate practice". In this study, for confirmatory hypothesis testing, naive practice was 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 have used 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" were calculated by multiplying respective practice time with game-specific career length.

A) **Naive practice** and

B) **deliberate practice** was measured with a new instrument, presented in Table 2.

Game-specific career length was 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** was measured using the Visual search task[1] available on the PsyToolkit software (Stoet, 2010, 2017) and operationalized as the average response time across all *correct* trials and for exploratory analysis as percentage of errors (Treisman & Gelade, 1980).

D) **speed of decision making** was measured using the Stop signal task[1] available on the PsyToolkit software (Stoet, 2010, 2017) and operationalized as the percentage of successful stops in no-go trials and for exploratory analysis as the percentage of correct trials[2] (combination of correct go actions in go trials and correct withholding of actions in no-go trials).

E) **reaction time** was measured using the Deary-Liewald task[1] available on the PsyToolkit software (Stoet, 2010, 2017) and operationalized as the average simple reaction time in *correct* responses and for exploratory analysis as choice reaction time.

F) **teamwork** as a perceived ability to work with others to achieve common goals was 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** was 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" was 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 have also measured 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 were analyzed by a robust linear regression analysis in R software using the *MASS* package (Venables & Ripley, 2002) and *rlm* function with MM method. Equiva-

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/

2 We have changed the exploratory operationalization of decision-making from using the total number to using percentages. This adjustment has not affected the results but has made data processing easier, as the results were provided as part of the Psytoolkit output in this format.

Table 2. 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* aim at improving **esports rank/skills**. 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).

lence testing was calculated in each case when SESOI was 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 were omitted from analyses. Missing data (except demographic data and cognitive variables) were 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 had a reason to treat the latter as mediators between age → rank and practice → rank. They were modeled separately to avoid producing biased estimates in the respective effects (see Wysocki et al., 2022). Accordingly, we have tested our hypotheses with two separate regression equations, which were 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, needed to meet the SESOI in each model to corroborate the respective hypotheses.

We considered H1a, b and H2a, b, e, f, g, h, i (with single-regression variables) corroborated if the point estimate of the effect exceeded r = .3 (with p < .01) in CSGO and r = .2 (with p < .01) in LoL, and the null corroborated if equivalence testing (Lakens, 2017) proved the absence of effect r > .3 in CSGO or r > .2 in LoL. In the case of neither, we deemed the results inconclusive. Unlike the above, H1c is corroborated only if we witnessed an effect r < .3 and equivalence testing suggested the absence of effect.

We considered H2c, d, j, k (with two-regression variables) corroborated if the point estimate of the effect exceeded 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) proved the absence of effect r > .3 in CSGO or r > .2 in LoL in both regressions. In the case of neither, we deemed the results inconclusive.

We have treated the results for Fortnite as exploratory.

Outcome-neutral control

For LoL respondents, ranking was 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 were used.

Data quality checks

To account for careless responding we have employed two specific items: 1) Bogus item: "I have been paid bi-

Table 3. Descriptives

	Counter-Strike: Global Offensive			League of Legends		
N / *N* after data quality checks / % of data missing	186 / 172 / .003			411 / 376 / .003		
number of males / females / non-binary / NA	155 / 14 / 1 / 2			311 / 56 / 7 / 2		
Variables	*M*	*SD*	range or/and ω_{total}	*M*	*SD*	range or/and ω_{total}
age	25.5	5.5	19-55	26.3	6.2	18-63
gamerank	12.2	4.7	1-18	15.5	5.2	1-27
career length (years)	7.6	4.3	0-23	6.8	3.3	0-15
practice (hours)	278.6	418.6	0-2688/ .80	211.7	303.2	0-2400/ .85
deliberate practice (hours)	266.3	456.5	0-3920/ .76	183.1	336.7	0-3000/ .79
attention (ms)	921.1	189.1	606.26-1836.8	954.5	204.2	598.3-2802.1
speed of decision-making (% of successes)	75.3	19.4	0-100	75.8	21.9	0-100
reaction time (ms)	265.7	41.7	195-447	270.8	39.1	146.1-471.3
team work	30.4	4.6	19-40/ .83	29.9	5.1	15-40/ .86
intelligence	3.7	1.6	0-6/ .86	4.1	1.5	0-6/ .80
persistence	17	3.5	10-25/ .77	16.9	3.8	5-25/ .83
Exploratory variables	*M*	*SD*	range or/and ω_{total}	*M*	*SD*	range or/and ω_{total}
attention - (% of errors)	3.6	6.1	0-60	3.4	6.7	0-54
speed of decision-making - (% of correct trials)	85.8	14.9	0-98.4	84.7	18.5	0-100
HW quality (PC)	3.5	.7	1-5	3.4	.8	1-5
HW quality (mouse)	3.6	.8	1-5	3.3	.9	1-5
HW quality (keyboard)	3.3	.9	1-5	3.2	.9	1-5
ping (ms)	41.4	45	1-300	49.3	31.8	5-217
physical training (mins/day)	47.8	41.9	0-300	46.7	42.2	0-400
ADHD	10	4.1	1-21/ .77	10.3	4.4	0-24/ .80
gaming disorder	8.7	3.4	4-18/ .87	9	3.6	4-20/ .89

Note: ω_{total} (McDonald omega total coefficient) = estimate of total-score reliability

weekly 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 have also used Mahalanobis distance statistic. Participants who failed at least 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.

Results

Descriptives

Sample characteristics, descriptive statistics, reliabilities, and missing data information are available in Table 3 and correlations between all variables in Table 4.

Outcome-neutral control

Participants provided their ranking at the beginning of the survey (measurement 1 of DV) and also at the end of the survey (measurement 2 of DV). In the second measurement of the DV, icons were used instead of text for LoL, and the order of ranks was reversed for CSGO and Fortnite. High correlations between measurement 1 and measurement 2 (CSGO, r = .99 and LoL, r = .96) supported their reliability.

Regression analyses

Table 5 presents the results of the robust linear regression analysis examining the relationship between long-term esports success and nine different psychological and non-psychological predictors.

Exploratory analyses

We have tested all four models for multicollinearity. VIF coefficients and correlograms (available in supplementary

Table 4. Correlation matrix between dependent variable and predictors

Variable	age	practice	deliberate practice	gamerank	reaction time	decision making	attention	intelligence	persistence	teamwork
age		.16 [.10, .22]	-.03 [-.09, .03]	-.32 [-.37, -.26]	.39 [.34, .44]	.06 [.00, .13]	.25 [.19, .30]	-.22 [-.28, -.16]	.26 [.20, .32]	.10 [.04, .16]
practice	-.12 [-.18, -.06]		.36 [.31, .42]	.13 [.07, .19]	-.09 [-.16, -.03]	.01 [-.05, .07]	-.02 [-.08, .04]	.04 [-.03, .10]	-.03 [-.09, .03]	-.03 [-.10, .03]
deliberate practice	-.02 [-.08, .04]	.35 [.30, .41]		.10 [.04, .16]	-.04 [-.10, .02]	-.09 [-.16, -.03]	-.11 [-.17, -.04]	-.08 [-.14, -.01]	.03 [-.03, .09]	.02 [-.04, .08]
game rank	-.23 [-.28, -.17]	.28 [.22, .34]	.15 [.09, .21]		-.30 [-.36, -.24]	.04 [-.02, .11]	-.37 [-.42, -.31]	.32 [.26, .37]	-.05 [-.11, .01]	.05 [-.01, .11]
reaction time	.11 [.04, .17]	-.13 [-.19, -.07]	.05 [-.01, .11]	-.19 [-.25, -.13]		-.04 [-.10, .02]	.42 [.37, .47]	-.23 [-.29, -.17]	.15 [.09, .21]	.07 [.01, .13]
decision making	-.22 [-.27, -.16]	-.01 [-.07, .05]	-.04 [-.10, .02]	.18 [.12, .24]	-.21 [-.27, -.15]		.05 [-.02, .11]	.07 [.01, .13]	.18 [.12, .24]	.11 [.05, .17]
attention	.11 [.05, .17]	-.01 [-.08, .05]	.04 [-.03, .10]	-.16 [-.22, -.10]	.31 [.25, .36]	-.20 [-.26, -.14]		-.30 [-.36, -.25]	.04 [-.03, .10]	.01 [-.05, .08]
intelligence	-.20 [-.26, -.14]	.02 [-.04, .08]	-.11 [-.17, -.05]	.11 [.05, .17]	-.11 [-.17, -.04]	.23 [.17, .29]	-.24 [-.30, -.19]		-.03 [-.09, .03]	.03 [-.03, .09]
persistence	.20 [.14, .26]	-.07 [-.13, -.01]	.10 [.04, .16]	-.01 [-.07, .05]	.04 [-.02, .10]	-.02 [-.08, .04]	.07 [.00, .13]	-.24 [-.30, -.18]		.37 [.31, .42]
teamwork	.07 [.00, .13]	-.08 [-.14, -.02]	.16 [.09, .22]	.00 [-.07, .06]	.12 [.06, .18]	-.04 [-.10, .02]	.06 [.00, .13]	-.17 [-.23, -.11]	.46 [.41, .51]	

Note: Pearson's correlation coefficients for CSGO are above the diagonal, while those for LoL are displayed below the diagonal.

Table 5. Results of regression analysis for CSGO and LoL

Predictor	Counter-Strike: Global Offensive [CSGO] (18 ranks)			League of Legends [LoL] (27 ranks)		
	β	95% CI	Result	β	95% CI	Result
Hypotheses 1a – b: expected positive effect *r* >.3 (CSGO) and *r* >.2 (LoL)						
practice	.20	-.01, .42	null confirmed	**.26**	.13, .40	confirmed
deliberate practice				-.01	-.15, .13	null confirmed
Hypothesis 1c: expected null by an equivalence test						
deliberate practice	.02	-.20, .24	null confirmed			
Hypotheses 2a - 2f: expected positive effect *r* >.3 (CSGO) or *r* >.2 (LoL)						
reaction time	-.16	-.32, .01	null confirmed	-.12	-.24, -.01	inconclusive
teamwork				-.01	-.13, .11	null confirmed
intelligence (Model 1)				.07	-.04, .18	null confirmed
intelligence (Model 2)				.01	-.10, .12	
persistence (Model 1)				.03	-.08, .14	null confirmed
persistence (Model 2)				.01	-.11, .12	
age	**-.33**	-.49, -.18	confirmed	**-.22**	-.32, -.11	confirmed
attention	**-.30**	-.46, -.14	confirmed			
Hypotheses 2g - 2k: expected null by an equivalence test						
teamwork	.06	-.09, .22	null confirmed			
intelligence (Model 1)	.21	.06, .36	inconclusive			
intelligence (Model 2)	.15	.00, .29				
persistence (Model 1)	.04	-.12, .19	null confirmed			
persistence (Model 2)	-.04	-.20, .12				
attention				-.07	-.19, .04	null confirmed
speed of decision making	.07	-.07, .21	null confirmed	.15	.04, .26	inconclusive

Notes: significant and above the SESOI effects are bolded. Inconclusive results: effects below SESOI but unable to confirm null by equivalence.

material: https://osf.io/2ptqf) do not point to a multicollinearity problem. After data collection, we noticed that some participants reported more practice time than 168 hours per week (all weekly hours). Although some of this can be explained by practice overlap, (multiple forms of practice can be done simultaneously), as an exploratory analysis, we have excluded these participants and carried out sensitivity analysis. This involved regression analyses that excluded participants who reported practicing for more than 168 hours per week, reducing the effective sample sizes from 172 to 142 participants for CSGO and from 376 to 319 participants for LoL. This did not have any meaningful effect on the results. The complete results of this sensitivity analysis are presented in supplementary Table 8 at https://osf.io/2ptqf.

The results of several regression analyses consisting of either alternative measures of practice, attention, speed of decision making, and reaction time, additional explanatory variables, or alternative dependent variables measured as the highest rank ever are available at https://osf.io/2ptqf. Out of all exploratory results, we highlight the effects of three variables: gender (CSGO, LoL) and intelligence (CSGO) appeared significant and above the coefficient equal to r = .20 in most of the models. Male gender and higher intelligence predicted better ranks. Lower ping as a predictor of better rank appeared significant in most models but rarely crossed the threshold r = .20.

Exploratory results for Fortnite are available at https://osf.io/vqyc9. Only deliberate practice in a regression calculated as a sensitivity analysis exceeded our SESOI.

Discussion

Our goal in this study was to seek confirmatory evidence to whether psychological predictors with previous evidence, including types of practice, actually predict esports success determined by rank. Almost none of the predictors received confirmatory support. In CSGO, the only corroborated psychological factor was *attention*, and in LoL *naive practice* was the sole relevant predictor. In both esports, younger *age* additionally predicted success. Taken together, the results suggest that success in esports is largely determined by multifactorial constructs that are either unknown or difficult to measure. We discuss each hypothesis respectively below.

H1: Practice and deliberate practice

The present findings did not confirm the application of deliberate practice theory to esports. In both CSGO and LoL null effects were confirmed with an equivalence test. Two caveats should be added to this finding. First, even though we carried out a thorough qualitative process with several validation steps to develop an esports-specific measure for deliberate practice, it is possible that the measure does not capture the full range of relevant deliberate practice routines. On the other hand, this issue can be considered a more general problem with deliberate practice theory and the construct itself, which is not clearly defined. For example, it has been suggested that differentiating between deliberate practice and practice is not useful, as indicated by a failed replication of the original Ericsson et al. (1993) study with a finding that best performers actually carry out less practice, including deliberate practice, than 'merely' good performances (Macnamara & Maitra, 2019). Second, we highlight again that the data represent a wide range of esports players and not professional players alone. Although deliberate practice theory should apply to sub-professional expertise too, advanced deliberate practice routines could be more prevalent among professionals (e.g., players with salaried contracts) and more large-scale analysis of exclusively professional practice could lead to different findings. Nevertheless, there are also good reasons to consider the present findings simply reflecting a reality where success in esports—as new cultures of competition—is not yet determined by any deliberate practice habits but rather a combination of other factors. In other words, the cultures of esports might not be sufficiently developed to enable players utilize efficient deliberate practice routines yet (see Ericsson & Pool, 2016, Chapter 4).

Another potential explanation could be that deliberate practice yields delayed benefits, which are not yet visible in the participants' ranks. For instance, Abbott et al. (2022) interviewed high-ranked LoL players who were aware of the need and importance of focusing on deliberate practice but still devoted most of the time they had set aside for practice to playing as many ranked matches as possible. The players felt pressure to do so by the broader ecosystem surrounding LoL, in which the quality of a player is viewed through a rank that players can increase and maintain only by winning ranked matches. It is possible that such patterns distort the relationship between ranked success and practice in esports.

Naive practice, in turn, was confirmed to have a large meaningful predictive effect (r = .3) in LoL. The effect was smaller (r = .13) in CSGO and the equivalence test, too, supported a null. These interesting cross-title differences could be explained by various explanans. Because we measured success by rank, differences in ranking systems could contribute to the practice effect. For instance, in LoL climbing a rank requires winning additional promotion matches, which adds to the amount of "naive practice" required to be successful rank-wise. Due to the hidden ranking algorithms in both titles it remains impossible to fully assess between-title differences, but a more in-depth analysis of each ranking system could help in future comparisons. We also entertain the possibility that the function of practice in CSGO is simply different or lesser compared to LoL. After preregistration, we found two new longitudinal studies and both are consistent with the above explanation: neither found any significant relationship between performance in CSGO (measured as Kill/Death ratio and tournament success) and the amount of practice (Pluss et al., 2021, 2022).

Furthermore, it has been previously suggested (Karhulahti, 2020) that the optimal amount and type of practice to improve one's performance in LoL depends on the role choice (support, midlane, etc.) and the current skill level; namely, practice is not a *linear contributor* to success. Because the effects witnessed in this study largely operate with averages, they may also reflect a reality where the *general* effect of practice in CSGO is factually small—yet, at the same time, practice can have *specific* large effects after a certain base level or moving to learn a new role. Notably, such dynamics are very likely to operate differently in LoL, which is an exceptionally information-heavy esport with thousands of ever-changing game mechanisms such as champion abilities and item details to learn. In other words, a high rank in LoL might require exceptional practice amounts *in general* because any success entails integrating large amounts of unique, game-specific information constantly being updated. We return to this new hypothesis later.

H2: Expected predictors of success

In this study, the clearest finding by far is the role of young age as a predictor of success in both esports. Although known psychomotor declines are likely to explain the finding at least partially, similar results have recently been obtained also in games like chess (Vaci et al., 2019), which do not evaluate psychomotor performance at all. This could be further explained by age-related decline in achievement motivation (Hustinx et al., 2009), which is consistent with Hedlund's (2020) observation that young esports players are the most competitive. In our present data, which come from psychomotorically demanding esports (CSGO and LoL), age-related decline in cognitive abilities such as attention (Vallesi et al., 2021) remains a strong candidate for explanation. On the specific levels of our esports—which are team-based and require continuously reintegrating new information—we additionally suggest that the social worlds of younger players tend to be tangled more tightly around esports (Meriläinen & Ruotsalainen, 2023), thus leading to intensive, "collateral" social learning. For younger players, esports may be a more holistic part of their daily interests and social life, which perhaps serves as an invisible contributor to their esports knowledge that, in turn, helps them keep up with the rapidly evolving game changes and updates.

A second positive confirmatory result was found with attention, which predicted success in CSGO (r = .32). As expected, the effect was not meaningful in LoL (r = .11). We operationalized attention through a classic visual search test where targeted objects are surrounded by distractors with similar features and must be identified. Although a test like this cannot be said to measure a single clear-cut construct, visual search corresponds to what typically players of FPS games like CSGO do under heavy time pressure. This is consistent with and further adds to previously discussed title differences: in an information-heavy esport like LoL, attention skills are not as relevant as in CSGO. Again, the results are based on general player populations and predicting success in a specific role or rank level could be different. E.g., it would not be surprising if the effect of attention would be meaningful for LoL carry roles. Moreover, according to earlier research, the ability to quickly identify targets on the monitor increases at lower skill levels, whereas at higher levels mainly the verification phase (target confirmation) and the subsequent movement speed becomes relevant (Toth et al., 2023). After a certain rank, attention might become more predictive of success if measured differently.

The remaining four constructs that were expected to meaningfully predict success—intelligence (in LoL), reaction time (in CSGO/LoL), teamwork (in LoL), persistence (in LoL)—did not receive corroborating evidence. Of these, the results regarding reaction time (in LoL) remained inconclusive. Taking into account the supporting evidence in Onate et al. (2023) and our own exploratory analyses, more research is required for this finding to be better understood. Teamwork (in LoL), persistence (in LoL), intelligence (in LoL), and reaction time (in CSGO) in turn, were all found null based on equivalence testing, which suggests that their independent success predicting role is minor at best. In fact, during the revision of this article, we discovered one more study where a null effect was found, too, for intelligence as a predictor of Dota 2 performance (Röhlcke et al., 2018).

H3: Expected non-predictors of success

We were able to confirm a null for the predictive effects of persistence, speed of decision making and teamwork ability in CSGO. In LoL, we were not able to confirm the null for attention nor speed of decision making; the results remained inconclusive. Likewise, the effect of intelligence was inconclusive in CSGO and, in fact, the witnessed point estimate effects (r = .23, r = .29) were very close to what we considered meaningful. The role of intelligence in esports calls for more research and we would especially welcome work that operationalizes the construct by using either multiple measures or multiple components (verbal comprehension, spatial reasoning, etc.).

Implications: Information density theory

Based on the present study, deliberate practice is not a meaningful predictor of long-term success in esport like CSGO or LoL. However, the study confirms that "naive practice", which is not deliberately organized, significantly predicts long-term success in LoL, which is an exceptionally information-heavy esport especially compared to CSGO. This opens a theoretical door to approaching esports through their information density: the amount of knowledge relevant for title-specific performance significantly affects the degree to which practice can improve long-term success. This has several implications. When the learning of large information loads has a central role in any esport, this logically dilutes the effects of other predictors compared to different esports titles. In the present data, this mechanism potentially explains why none of the predictors beyond young age were meaningful in LoL but in CSGO both attention and gender (exploratorily) were. We hypothesize that in LoL—due to its information density—the amount of practice is so essential that the significance of other predictors becomes meaningful only at the very highest levels of competition.

If the theory is true, a predictor like attention that was confirmed to be a strong predictor for CSGO success would be a less meaningful predictor of success in a mechanically similar FPS such as Overwatch, as the latter (with 37 unique heroes and 24 maps) has higher information density, which increases the relevance of naive practice and dilutes the relevance of attention. At least partially, this information density theory might also explain why experts of information-light CSGO stress the vague "game sense" as a core determinant of skill (Sharpe et al., 2022). The theory is also consistent with the idea that long-term success in most esports—that operate as constantly evolving and updating information systems—is more determined by naive practice in comparison to traditional team sports, which tend to have almost zero information density (i.e., their rules can be learned in no time after which improvement is determined by deliberate or technique-focused learning). This comparison is tricky nonetheless because the physical requirements of traditional team sports add an extra layer of complexity when comparing their practice routines to esports. We look forward to developing the conceptual clarity of esport information density, its measurement, and testing the theory in the future.

Limitations

We believe that success in CSGO might be significantly affected by previous (FPS) genre convention knowledge or literacy, which can partially explain why the respective practice effects were small. It is also worth reminding that our data involved players of all skill levels, whereas certain practice effects might concern only specific skill levels. In addition, we noticed that some participants reported more than 24 practice hours per day (168 hours per week). Although it is possible to be simultaneously involved in multiple practice activities, it may also be that some players felt they devoted more time to a given activity than they actually did. We further note that 'naive practice' and 'deliberate practice' constructs remain vaguely defined in the literature (e.g., Macnamara & Maitra, 2019), which makes it difficult to comprehensively assess construct validity. Finally, our SESOIs may have been suboptimal and it is possible that, for some people, the observed effects are meaningful even though we did not consider them as such (and vice versa).

Conclusions

This study adds falsifying evidence for the applicability of deliberate practice theory to esports, yet corroborates the relevance of non-deliberate, naive practice as a predictor of long-term success in information-heavy esports such as League of Legends. On the other hand, attention—as operationalised by a visual search test—was predictive of success in Counter-Strike but not in League of Legends. We propose *information density theory* as a means to explain how distinct faculties can be relevant for different esports that operate by varying degrees of performance-critical information. The study also confirms young age as a meaningful predictor of success in both Counter-Strike and League of Legends, but calls for more research to better understand the underlying aging mechanisms that contribute to esports success. Ultimately, the findings imply that long-term success in any esport is a result of numerous small factors that together form different networks of performance. Most of those factors and their functionality remain unknown, and future research should move from simple latent models to exploring title-specific complex systems.

Contributions

Contributed to conception and design: MM, VMK, MA
Contributed to acquisition of data: MM, YJ
Contributed to analysis and interpretation of data: MM, VMK, MA
Drafted and/or revised the article: MM, VMK, YJ, MA
Approved the submitted version for publication: MM, VMK, YJ, MA

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Competing interests

VMK is one of the Peer Community In: Registered Reports recommenders.

Data accessibility statement

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

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