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Processing Speed, Not Multitasking, Drives Expert Decision-Making Under Pressure

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Abstract

The cognitive mechanism underlying high performance during decision-making under pressure – such as in first-person shooter (FPS) games – is still unclear: advantages in multitasking or general processing speed? To resolve this, we classified $N = 230$ players (16-34 years) of the video game Counter-Strike into four expertise clusters (Novice, Skilled, Emerging, Expert), assessing their processing speed and task-switching performance. To better understand the source of expertise effects, we used drift-diffusion modelling (DDM) to estimate non-decision and decision components of performance. Experts exhibited significantly faster reaction times than Novices, but no specific multitasking advantage was observed. The DDM revealed that this speed advantage was driven by higher drift rates and shorter non-decision times. No expertise-related differences were found in boundary separation, the strategic component of decision-making. Findings suggest that expert performance in decision-making under pressure is characterised by advantages in general processing speed rather than being associated with greater multitasking capabilities.

Keywords: processing speed; multitasking; decision making; expertise; video games

Public Significance Statement

This study resolves a key debate in expertise research: are high-performing first-person shooter (FPS) players better at multitasking, or are they just generally faster? We examined the performance of 230 players of the video game Counter-Strike, ranging from novices to experts. We found that experienced FPS players are indeed faster at reacting to tasks than novices but are not better at multitasking. Using computational modelling, we determined that this speed advantage is driven by faster evidence accumulation and higher perceptual-motor efficiency. This means that expert FPS players are faster at three fundamental steps: a) understanding and processing what is shown on the screen (i.e., encoding information), b) more efficiently accumulating information to reach a decision, and c) responding to information by pressing the response button (i.e., executing a motor response). These findings suggest that the primary cognitive profile of FPS experience is an advantage in overall processing and decision-making speed, which could be beneficial in other fast-paced, dynamic and high-stakes tasks, such as emergency response and air traffic control.

Processing Speed, Not Multitasking, Drives Expert Decision-Making Under Pressure

The ability to make rapid and accurate decisions under pressure is essential to human performance, particularly in high-stakes contexts, such as emergency response and air traffic control. However, ethical and practical constraints make it exceptionally challenging to observe and quantify the cognitive mechanisms underlying decision-making speed in these real-world, high-stress environments. First-person shooter (FPS) games, a highly popular and cognitively demanding subgenre of action video games, provide precisely this ecologically valid and controlled *sandbox* to examine the underlying mechanisms of decision-making under pressure. Given their capacity to engage a broad range of cognitive abilities in a controlled yet immersive setting, FPS games provide an ideal context for investigating cognitive functioning (Campbell et al., 2018).

Indeed, a growing body of research has identified a positive association between action video game play and performance on cognitive tasks (Bediou et al., 2018, 2023). This relationship is hypothesised to arise from the high cognitive demands of video games, particularly FPS games, which immerse players in fast-paced, dynamic environments that require continuous monitoring of incoming stimuli, rapid decision-making, and the simultaneous management of multiple objectives. While some studies question the strength of this relationship (Sala et al., 2018), the prevailing view is that playing FPS games requires, and may potentially even enhance, cognitive skills. However, the specific mechanism of this expertise advantage is debated. This study uses a large cross-sectional sample of FPS players and computational modelling to determine the cognitive driver of FPS expertise in decision-making under pressure.

Multitasking and Processing Speed in FPS Players

Cross-sectional research suggests that FPS players outperform non-video game players in the ability to efficiently shift attention between different tasks (hereafter referred to as multitasking), a cognitive skill which is essential both for everyday activities, such as cooking, and for high-pressure professions, such as emergency medicine and air traffic control (Boot et al., 2008; Cain et al., 2012; Colzato et al., 2010; Green et al., 2012; Strobach et al., 2012). However, it remains unclear whether

this observed advantage in multitasking reflects superior multitasking abilities or rather is primarily attributable to differences in general processing speed (Dobrowolski et al., 2015). General processing speed refers to the rate at which individuals perceive, interpret, and respond to sensory information. Indeed, processing speed is fundamental to efficient performance in time-sensitive tasks, particularly those which require decision making under pressure (Salthouse, 1996, 2000). Although the current cross-sectional design cannot distinguish between a causal training effect (where playing FPS games enhances processing speed) and a selection effect (where individuals with naturally faster processing speed are more likely to play and excel in FPS games), identifying the specific cognitive parameters that differ between expertise groups is a necessary step in understanding the nature of the FPS advantage.

To investigate multitasking, researchers often use a task-switching paradigm, in which participants perform simple decision-making tasks either separately in single-task blocks or in rapid succession in mixed-task blocks. This measures two indices of multitasking: switching and mixing costs. Switching costs are the typical decrement in reaction time (RT) observed when participants switch tasks compared to when they repeat a task. Mixing costs, on the other hand, measure the difference in RTs between maintaining readiness for multiple tasks in a mixed block relative to completing just one task in a single block. However, a significant challenge of this approach is that many studies compute these costs using absolute RT differences (see von Bastian et al., 2020). The problem with this approach is that it inherently confounds switching and mixing costs with differences in general processing speed (e.g., see Druey & von Bastian, 2017). For example, if participant A is generally faster, they may show a mean RT of 600 ms in switch trials and 400 ms in repetition trials, yielding an absolute switching cost of 200 ms. Participant B may be generally slower, with 900 ms in switch trials and 600 ms in repetition trials, resulting in a 300 ms switching cost. However, proportionally, both participants exhibit precisely the same cost: $400/600 \text{ ms} = 600/900 \text{ ms} = 0.66$. Hence, it is entirely possible that the superior multitasking performance observed in FPS

players relative to non-players is a result of their faster general processing speed (see Dobrowolski et al., 2015).

FPS players are indeed known to demonstrate faster processing speed than non-game players (Dale & Green, 2017; Green et al., 2010; Karle et al., 2010; Schubert et al., 2015; but see van Ravenzwaaij et al., 2015). However, using RTs alone as a measure of processing speed is problematic. RT differences reflect a combination of underlying cognitive components rather than a single process (see also von Bastian et al., 2022). For example, FPS players' faster RTs could reflect quicker motor responses given their extensive training in using computer peripherals (Warburton et al., 2023), or they could instead reflect a deliberate strategic choice to prioritise speed over accuracy. If we hope to disentangle the precise relationship between multitasking and processing speed performance advantages in FPS players, we must move beyond simple aggregate RT measures.

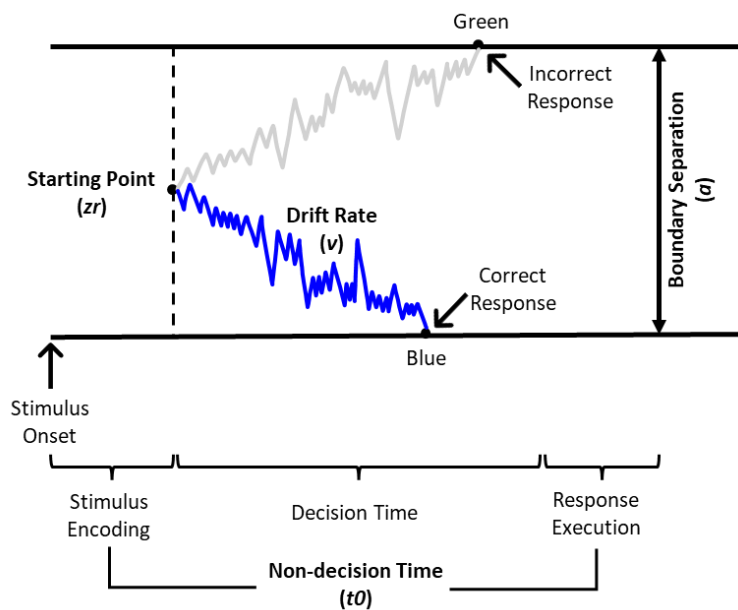
Drift-Diffusion Modelling

One such approach is the application of the drift-diffusion model (DDM), which utilises both RT distributions and accuracy rates to estimate interpretable decision-making parameters (Ratcliff, 1978; Ratcliff & McKoon, 2008; see also Reinhartz et al., 2023). Figure 1 illustrates these components. In a typical two-choice task (e.g., deciding whether an object is green or blue), the DDM assumes that initial stimulus encoding is followed by a period of noisy evidence accumulation. This process continues until a decision threshold is reached, prompting a response. While the DDM was originally developed for simple decision-making tasks, it has also been validated in the context of task-switching (Schmitz & Voss, 2012; 2014) to decompose the complex cognitive demands of shifting between mental sets (Cohen Hoffing et al., 2018; Karayanidis et al., 2009). Implementations of the model estimate four key parameters: drift rate (v), reflecting evidence accumulation; boundary separation (α), reflecting response caution; non-decision time (t_0), accounting for pre- and post-decision processes such as stimulus encoding and motor execution response; and starting point (z_r), representing baseline response bias. In cued task-switching, non-decision time also encompasses task-set reconfiguration and residual cue processing (Schmitz & Voss, 2012; 2014). By applying this

model to RT and accuracy data from FPS players, we can determine whether performance advantages arise from faster evidence accumulation (i.e., higher drift rates), from a strategic preference for speed over accuracy (i.e., narrower boundary separations), or from more efficient pre- and post-decision processes such as encoding, response execution and task-set reconfiguration (i.e., shorter non-decision time).

Figure 1

Illustration of the Drift-Diffusion Model



Note. The model conceptualises decision making as a noisy accumulation of evidence between two decision boundaries, in this example, between two possible colours of the shape. Drift rate (v) represents the slope of the evidence accumulation process, with a higher drift rate suggesting faster evidence accumulation. Boundary separation (α) denotes the trade-off between speed and accuracy, with wider boundaries indicating more response caution. Non-decision time (t_0) captures processes unrelated to the decision itself, including stimulus encoding, task-set reconfiguration, and response execution. The starting point (zr) indicates any initial bias towards one response, with a centrally located starting point indicating no bias towards either option. Two drift rates are shown for illustration purposes, but only a single drift rate was estimated per participant per condition.

Despite its potential, the DDM has been used sparingly in video game research and with mixed results. For example, an influential correlational study by Green et al. (2010), while a significant early contribution, was based on a relatively small sample ($N = 11$ action video game players, $N = 12$ non-gamers). In a visual motion direction discrimination task, the authors found that action video game players had higher drift rates, indicating more efficient evidence accumulation, and narrower boundary separations, suggesting a speed-accuracy trade-off. They found no differences in non-decision time. However, these findings have been difficult to replicate. Subsequent DDM research has used different methodologies, such as a video game training study (van Ravenzwaaij et al., 2014) and an emotion perception task (Pichon et al., 2020) and has not found the same DDM parameter differences in video game players. Thus, there is a clear need for larger-scale correlational studies to more definitively examine the relationship between video game experience and DDM parameters.

Challenges in Video Game Research

There is a growing body of research exploring the relationship between video gameplay and cognitive performance, which has been crucial in establishing a link between video games and cognitive performance. However, there are some key methodological considerations that future studies can address to build upon this foundation. First, previous research has often grouped different game genres together. This approach, while a good starting point, may not fully capture the unique cognitive demands of specific game types. This lack of specificity is problematic, as different game genres place unique demands on cognitive abilities, and conflating different game genres may therefore obscure or dilute the specific cognitive benefits of a particular game type. Moving forward, differentiating between genres, for example, by looking at a game's perspective and movement style (e.g., first-person vs. third-person), will allow for a better understanding of the specific cognitive benefits each genre may offer (Smith & Basak, 2023). This more nuanced approach will help uncover the precise relationships between distinct gameplay experiences and cognitive abilities.

Second, much of the existing literature has tended to focus on relatively novice video game players, whose limited experience may not capture the cognitive associations with more extensive gameplay. Studies typically classify participants as video game players if they play for approximately 5 hours per week (Bavelier et al., 2012; Bejjanki et al., 2014; Colzato et al., 2010; Dobrowolski et al., 2015; Strobach et al., 2012). Yet, the average weekly playtime of habitual video game players is considerably higher than this, with one study reporting an average of 13.50 hours per week (Sobczyk et al., 2015). Indeed, esports athletes – that is, semi-professional or professional players who often compete in video games in high-stakes international competitions, sometimes as their primary occupation – play even more extensively and, so, may well exhibit different cognitive profiles than novice players. Research should therefore encompass the full spectrum of experience, from novices to esports professionals, to provide a more complete picture of the cognitive correlates of gaming across different levels of expertise.

Finally, many studies rely on self-report measures of gaming experience, such as asking players to report their perceived skill level (Appelbaum et al., 2013) or an estimate of weekly playtime (Dale & Green, 2017; Gobet et al., 2014). While these self-reports have been useful, a more robust approach would involve incorporating objective in-game metrics that are less prone to biases due to individual differences in memory, introspection, and/or metacognition. Modern video game platforms provide detailed metrics such as total playtime, skill level (often using ranking systems similar to the Elo rating system in chess), and in-game performance indicators like shooting accuracy, or the ratio of how many times the player killed others in-game vs. died themselves (Gong et al., 2015; Kim et al., 2015; Latham et al., 2013; Stafford & Vaci, 2022; Tanaka et al., 2013; Toth et al., 2021). Utilising these objective measures can provide a more accurate and comprehensive index of a player's expertise, allowing for building on the knowledge gained from earlier studies with more robust data. Addressing these methodological limitations by focusing on specific game genres, including a wide range of player experience, and utilising objective in-game metrics, is essential for advancing understanding of how video game play relates to cognitive functioning.

The Present Study

We aim to address these previous challenges by adopting a multifaceted approach to investigate multitasking, processing speed and decision-making performance in FPS players. We chose Counter-Strike (Valve Corporation, 2025; see Figure 2) as our FPS game of interest for two key reasons. First, as one of the longest-running and most popular multiplayer FPS games, Counter-Strike has a large and diverse player base, with an all-time peak of over 1.8 million players (www.steamcharts.com), which allows for recruiting a large sample ($N = 230$). Second, as a major competitive esports title, Counter-Strike attracts players ranging from complete novices to highly experienced individuals competing at the highest skill levels. This wide range of expertise is a significant strength of our sample.

Figure 2

Screenshot of Counter-Strike Gameplay



Note. Counter-Strike gameplay demands rapid decision making and multitasking. Players must process enemy positions while shifting their attention between the mini-map (top left) and monitoring critical resources like weapons and ammunition (bottom right), and match statistics (top middle).

To avoid reliance solely on subjective self-reports, we adopted a mixed-method approach to classify FPS expertise. First, we conducted in-depth semi-structured interviews with Counter-Strike players to develop a comprehensive questionnaire which assessed several dimensions of FPS expertise, including lifetime playtime (total hours of playtime), current playtime (hours of playtime over the past week), Counter-Strike skill (in-game ranking), and self-rated expertise. We then used a data-driven *k*-means cluster analysis to identify and group players into four levels of expertise based on their expertise in these dimensions.

To move beyond the limitations of RT difference measures, we utilised the DDM to evaluate the theoretically interpretable cognitive processes underpinning decision making. This computational modelling approach allowed for determining whether player advantages arise from faster evidence accumulation (higher drift rates), from a strategic shift towards faster, less cautious decisions (narrower boundary separation), or from quicker encoding and response execution (shorter non-decision time). Finally, by administering a task-switching paradigm, our methodology directly addresses the central ambiguity in the literature: whether FPS players are truly better at multitasking or simply faster, and what specific cognitive mechanisms are responsible for their performance advantages.

Methods

We report how we determined our sample size, all data exclusions, all manipulations, and all measures in the study.

Participants

Associations between habitual video game play and cognitive performance typically range from $g = 0.40$ (Sala et al., 2018) to $g = 0.55$ (Bediou et al., 2018), which at $\alpha = .05$ at 90% power would require sample sizes ranging from $N = 52$ to $N = 95$ to detect significant correlations. In addition to statistical power, we also aimed to obtain stable correlation coefficients. Therefore, we followed Schönbrodt and Perugini's (2013) simulation-based recommendations of at least $N = 260$ to ensure stability at 90% power and a corridor width of $w = .10$. We successfully recruited 310

participants via social media posts on Counter-Strike community groups (e.g., Discord, Facebook) and by directly contacting professional and university Counter-Strike teams. This recruitment took place over four weeks, from 23/03/2021 to 21/04/2021. At the time of the study, participants played *Counter-Strike: Global Offensive (CS: GO)*, first released in August 2012, as *Counter-Strike 2* would not be released until September 2023.

All participants were required to meet the following inclusion criteria: 16-35 years old; self-reported proficiency in English to understand instructions and questions; played Counter-Strike with any frequency or experience; had access to a computer with an internet connection; normal or corrected-to-normal vision, including no colour blindness; no current diagnosis of neurological, psychological or psychiatric illness; no current medication with known side-effects on cognition; and no current recreational drug use (e.g., cannabis, cocaine, or methamphetamine). The first 300 participants were eligible for compensation with £4 Amazon e-vouchers. All participants, including those completing the study after the first 300 participants, were eligible to enter a prize draw for 1x £100, 1x £50, and 5x £10 Amazon e-voucher prizes.

After initial recruitment of 310 participants, we refined the sample by applying several exclusion criteria. Four participants were removed due to incomplete data in the experimental task ($n = 1$) or the questionnaire ($n = 3$). To ensure all participants had active Counter-Strike experience, we excluded 44 participants who reported no total hours of playtime ($n = 5$), no current Counter-Strike rank ($n = 10$), or who reported being *unranked* as their current Counter-Strike rank ($n = 29$). Additionally, we excluded four participants who reported being professional players of other FPS games (e.g. Call of Duty, Overwatch, Halo and Rainbow Six Siege) to avoid confounding our findings with expertise from other games. This ensured our analysis was specific to the cognitive profiles of Counter-Strike players. Two participants were removed who reported implausible values (e.g., "over 100" for weekly hours of playtime). Finally, to ensure sufficient task engagement, we excluded 26 participants who scored below 75% accuracy in the task-switching paradigm. These exclusions resulted in a final sample of $N = 230$ for the analyses. This final sample included 206 men, 21 women,

1 non-binary participant, and 2 participants who preferred not to report their gender. Participant age ranged from 16 to 34 years ($M = 21.94$ years, $SD = 4.72$).

Materials and Procedure

This cross-sectional online study was administered via Tatool Web, (www.tatool-web.com; von Bastian et al., 2013) and Qualtrics (www.qualtrics.com; Provo, UT). Ethical approval for this study was obtained from the University of Sheffield's Research Ethics Committee.

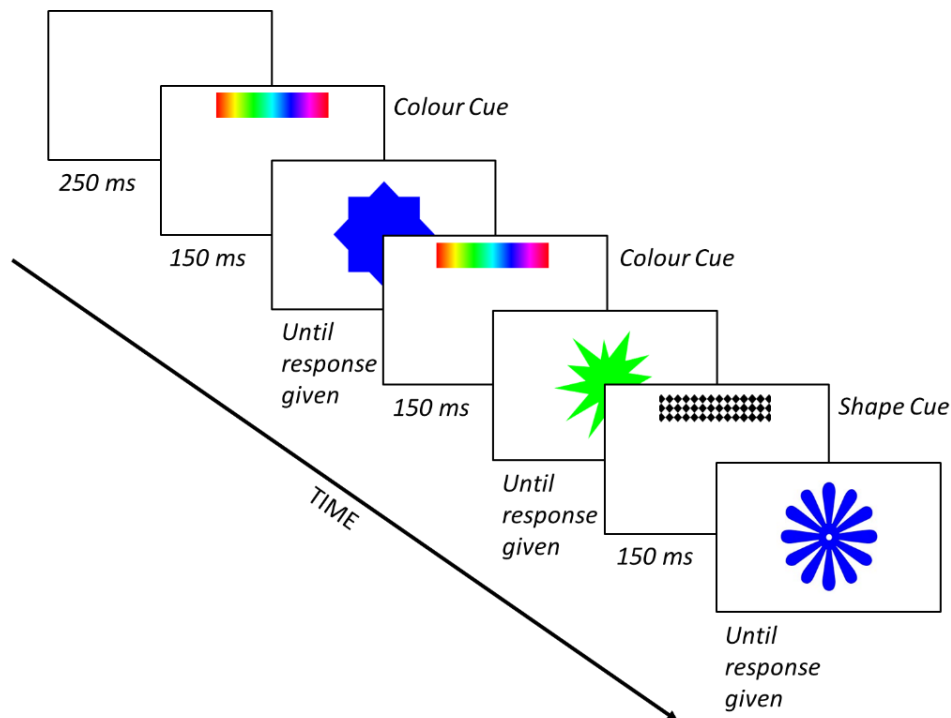
Task-Switching Paradigm

The task-switching paradigm is illustrated in Figure 3. Participants were shown simple geometric shapes and were asked to classify them in terms of their colour (green or blue) or shape (round or spiky), as quickly and accurately as possible. Stimuli were 16 round and 16 spiky shapes presented in either green or blue (64 stimuli in total). We used a “sandwich” design consisting of five blocks: two single-rule blocks (where stimuli were classified either by shape or by colour), a mixed-rule block (switching between colour and shape classification) and two final single-rule blocks in the reversed order (where stimuli were again classified either by colour or by shape). This widely employed design allows for assessing baseline processing speed, with the reversed order of single-rule blocks controlling for practice effects, as well as mixing costs by comparing performance in single-rule and mixing blocks, and switching costs by comparing performance in repetition and switch trials (Karch & Kray, 2009; Koch et al., 2018; Meiran et al., 2008; von Bastian et al., 2016). There were 256 single-rule trials (64 per block) and 129 mixed-rule trials. In addition, there were three 12-trial practice blocks, presented immediately before the first pair of single-rule blocks, before the mixed rule block, and before the second pair of single-rule blocks (36 practice trials overall). Each trial presented a 250-ms blank screen followed by a 150-ms task cue, after which the target stimulus was displayed until a response was given. In the single-rule blocks, participants were asked to classify the stimuli based on just one rule (i.e., either shape or colour). In the mixed rule block, the rules switched unpredictably. Half the trials were switch trials, in which the rule changed from the previous to the current trial (e.g., shape then colour). The other half of the trials were repetition

trials, in which the rule was the same on consecutive trials (e.g., shape then shape). The dependent variables were RT and accuracy (proportion correct).

Figure 3

Illustration of the Task-Switching Paradigm



Note. Illustration of the mixing block with an example of repetition (colour-colour) and switch (colour-shape) trials. In single-rule trials, the same rule was applied throughout the block.

Counter-Strike Expertise Questionnaire

Following the experimental task, participants completed a 29-item questionnaire regarding demographics (age, gender, and video game play across genres and titles) and Counter-Strike expertise (see Figure S1 in the Supplemental Materials). This questionnaire was developed based on semi-structured interviews with three players with different levels of Counter-Strike expertise: one participant self-identified as playing Counter-Strike only casually, another participant played intensively and aimed at a career in competitive gaming, and the third participant was a professional esports athlete. Based on these interviews, we identified four primary measures of Counter-Strike

expertise: total hours of playtime, weekly hours of playtime, self-rated expertise, and current in-game ranking.

The total hours of playtime reflected players' lifetime engagement with Counter-Strike. As Counter-Strike is distributed on the gaming platform Steam (Valve Corporation, 2025), total playtime is automatically logged, and that statistic is freely available to players, who were prompted to check and report these values. Weekly hours of playtime reflected current engagement with Counter-Strike, which participants were asked to approximate (for use of similar measures, see Bavelier et al., 2012; Cain et al., 2012; van Ravenzwaaij et al., 2014; Waris et al., 2019). Self-rated expertise was assessed on a rating scale from 0 ("casual Counter-Strike player") to 100 ("professional Counter-Strike player") and has been used extensively in the literature before (Appelbaum et al., 2013; Bialystok, 2006; Cain et al., 2014). The current ranking is an in-game measure of skill based on performance in competitive matches in Counter-Strike (referred to as matchmaking mode). The specific details of this ranking system are proprietary but broadly similar to the Elo system commonly used in chess (Gong et al., 2016; Toth et al., 2019). Players start from being *unranked* (coded as Rank 1) and are then ranked based on their performance in competitive games, ranging from *Silver I* (Rank 2) to *Global Elite* (Rank 19). Finally, participants were asked to self-report further contextual information, including additional play statistics and experiences. That information was not used in this analysis, but the questions are presented in Figure S1 in the Supplemental Materials.

Analysis

All analyses were conducted in R (R Core Team, 2025).

Data Pre-Processing

For the analysis of RTs, we first performed an initial broad trim, removing all responses with very fast (< 100 ms) or very slow RTs (> 10,000 ms). Next, we removed outliers, defined as values exceeding 3 median absolute deviations (MADs) from the median RT for each participant, task (colour, shape), and condition (single-rule, repetition and switch trials), and accuracy response (correct, incorrect). This trimming procedure reduced the overall number of trials from 118,656 to

105,243, excluding 13,413 trials (11.30%; see Table S1 in the Supplemental Materials for by-condition breakdowns). After trimming, RTs were log-transformed to reduce skewness and better approximate a normal distribution. For the behavioural analysis of RTs, only correct responses were retained, whereas all responses were used for the DDM. Following previous work using this paradigm (e.g., De Simoni & von Bastian, 2018; Guye & von Bastian, 2017; Karbach & Kray, 2009; Koch et al., 2005; Mack et al., 2025; Rubin & Meiran, 2005; von Bastian et al., 2016), the two single-rule tasks (colour and shape) were merged into a single measure.

Cluster Analysis

To describe the expertise of our sample and to investigate whether differences in Counter-Strike expertise were associated with cognitive performance, we applied a *k*-means clustering algorithm – a common unsupervised machine-learning method which groups data into distinct clusters based on their features. Participants were clustered using four Counter-Strike expertise variables, which were z-transformed prior to clustering, as *k*-means is sensitive to variable scaling. We used the ‘kmeans’ function from the ‘stats’ package (R Core Team, 2025) to define *k* cluster groups by minimising within-cluster variance and maximising between-cluster variance. To determine the optimal number of clusters, we used a consensus-based algorithm with the ‘n_clust’ function from the ‘parameters’ package (Lüdtke et al., 2020), which aggregates the results of 29 different clustering indices to find the consensus.

We assessed the quality and reliability of the cluster solution through several validation steps. Internal cohesion and separation were evaluated using silhouette plots generated using the ‘fviz_silhouette’ function from the package ‘factoextra’ (Kassambara & Mundt, 2020) and further verified with Principal Component Analysis (PCA) to confirm that clusters occupied distinct regions of the feature space. Cluster stability was evaluated using a bootstrapping procedure ($B = 100$) to calculate the Jaccard similarity index via the ‘clusterboot’ function from the ‘fpc’ package (Hennig, 2026). The generalisability of cluster rules was evaluated using an 80/20 split-half validation, in which a *k*-means model was trained on 80% of the data using the ‘kcca’ function from the ‘flexclust’

package (Leisch, 2006) to predict membership for the remaining 20% hold-out set, confirming the consistency of the silhouette coefficients. Finally, three-dimensional (3D) visualisations were created using the 'scatterplot3d' function from the package 'scatterplot3d' (Ligges & Mächler, 2003), to illustrate the distribution of participants in their clusters across the expertise dimensions.

Drift-Diffusion Modelling

Using the fast-dm-30 software (Voss et al., 2015), we estimated drift rate (v), boundary separation (α) and non-decision time (t_0) separately by condition for each participant. While a full seven-parameter DDM can incorporate trial-by-trial variability parameters (s_v , s_z , s_t), we omitted these to avoid over-parameterisation, prevent parameter trade-offs, and ensure stable, robust parameter estimation given our per-condition trial counts, an approach widely supported in task-switching modelling (Schmitz & Voss, 2012). Additionally, we used a fixed starting point (z_r) of 0.5 (equidistant between decision boundaries), as task rules and response options occurred with equal probability, assuming no prior response bias at trial onset. Maximum likelihood estimation (MLE) was chosen due to its efficiency in estimating a three-parameter model (where v , α , and t_0 are estimated) with uncontaminated data (Lerche et al., 2017). Data simulations show that a minimum of 40 trials is recommended for a three-parameter model using the MLE method (Lerche et al., 2017; Voss et al., 2015). Following data pre-processing, our data contained a minimum of 141 ($M = 231.37$, $SD = 11.11$) data points remaining for single-rule trials, 46 ($M = 58.50$, $SD = 2.84$) for repetition trials, and 51 ($M = 59.24$, $SD = 2.72$) for switch trials.

After parameter estimation, the construct-samples tool in fast-dm (Voss & Voss, 2007) was used to generate simulated datasets for each condition and participant based on the estimated DDM parameters. As Figure 4 illustrates, the simulated data closely matched the observed data, albeit slightly underestimating accuracy on single-rule trials. We also compared the three-parameter model with three models where one parameter (v , α , or t_0) was constrained to the mean value estimated from the three-parameter model for each condition (see Table S3 in the Supplemental Materials). The log-likelihood ratio test (χ^2) revealed that the three-parameter model fitted significantly better

than those models where one parameter was fixed; these results are presented in Table 1, suggesting that the three-parameter model outperformed the models where one parameter was fixed (see Figures S2-4 in the Supplemental Materials).

Table 1

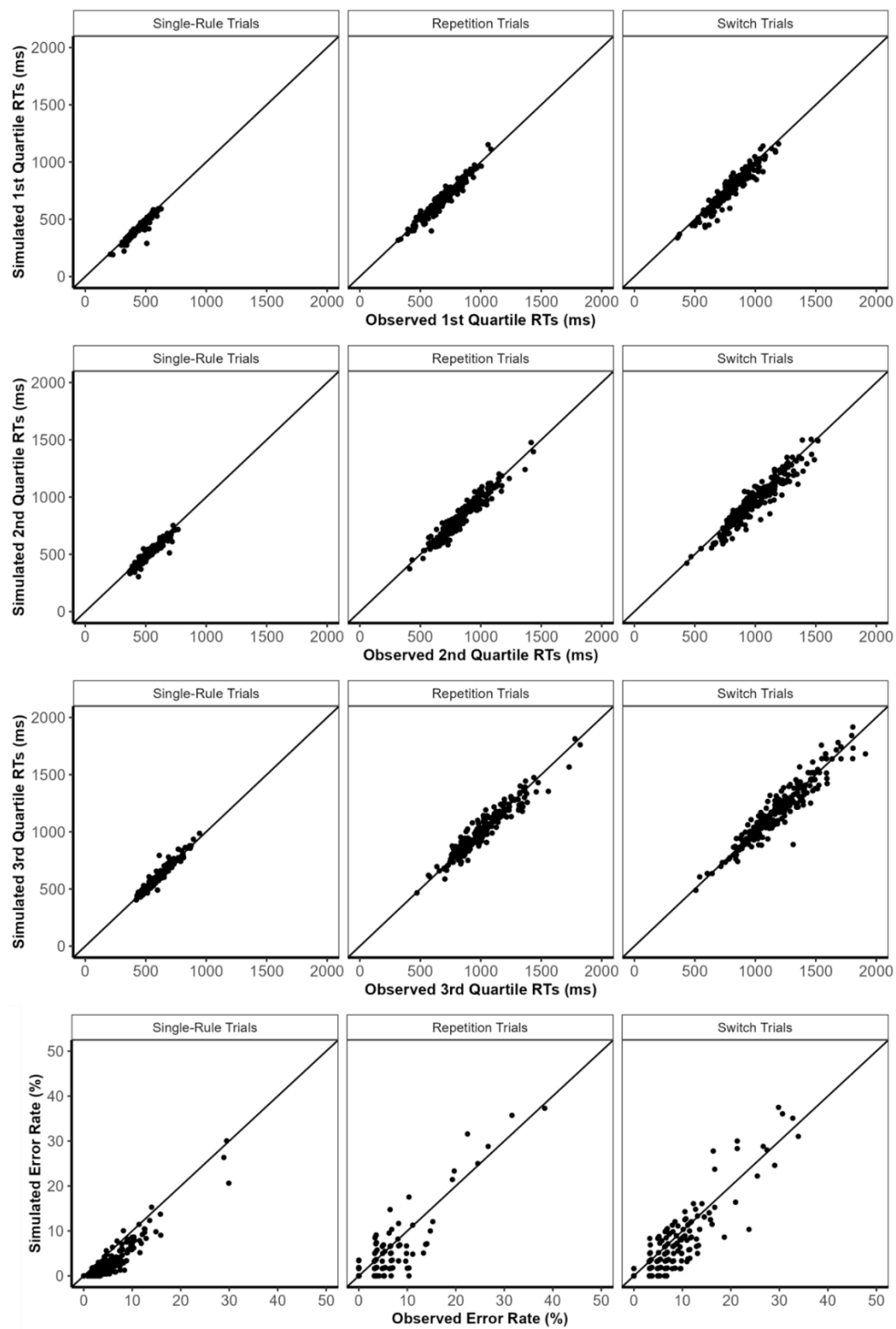
Log-Likelihood Ratio Test Model Comparisons

Model	<i>k</i>	χ^2	<i>p</i>	AIC	BIC
Three-parameter model	3			-102573.39	-102563.07
Fixed <i>v</i> model	2	77,642.21	< .001	-24933.18	-24926.30
Fixed <i>a</i> model	2	199,516.11	< .001	96940.72	96947.60
Fixed <i>t₀</i> model	2	86,443.00	< .001	-16132.39	-16125.51

Note. χ^2 and *p*-values are reported for the comparison of the three-parameter model against the

respective fixed-parameter models. The three-parameter model yielded a significantly better fit than

any of the restricted models. AIC: Akaike Information Criterion; BIC: Bayesian Information Criterion.

Figure 4*Illustration of Model Fit as a Function of Reaction Time Quartiles and Accuracy by Condition*

Note. RT = reaction time.

Statistical Analysis

Zero-order correlations between variables were analysed using the 'apa.cor.table' function from the 'apaTables' package (Stanley, 2024). Our study uses a mixed-model analysis of variance (ANOVA) to analyse the data, with a between-subjects factor (cluster) and a within-subjects factor (condition). Before running the ANOVA, we tested key assumptions for both types of factors. For the within-subjects factor condition, the assumption of sphericity was tested with Mauchly's test. When the assumptions were met, we performed a repeated-measures ANOVA using the 'aov' function from 'stats'. If the homogeneity of variance assumption was violated, degrees of freedom were adjusted using Greenhouse-Geisser correction. The mixed-model ANOVA was performed using the 'anova_test' function from the package 'rstatix' (Kassambara, 2023). For the between-subjects factor cluster, we used Levene's test with the 'leveneTest' function from the 'car' package (Fox & Weisberg, 2019), both overall and per condition (i.e., single-rule, repetition and switch). When significant effects were observed ($\alpha = .05$), we performed post-hoc pairwise comparisons to identify which specific groups differed. We used Bonferroni-adjusted comparisons using the 'pairwise_t_test' function from 'rstatix' if the homogeneity of variance assumption was met. When the assumption was violated, we used the Games-Howell post hoc test with the 'games_howell_test' function from 'rstatix'. For all significant post-hoc results, we computed Cohen's d effect sizes using the 'cohens_d' function from the package 'effectsize' (Ben-Shachar et al., 2020) to quantify the magnitude of the observed differences. To assess if age contributed to observed differences in cognitive performance between clusters, we conducted Analysis of Covariance (ANCOVA) models using the 'lm' function from 'stats', followed by the 'Anova' function from 'car'.

Bayesian Analysis

To complement our frequentist analyses, we used Bayesian statistics to provide evidence for either the alternative hypothesis (H_1) or the null hypothesis (H_0). We used the 'BayesFactor' package (Morey & Rouder, 2024) to compute Bayes Factors (BFs), which are robust to assumption violations. All priors were specified on standardised effect sizes. For main effects, we used 'anovaBF' with the

default Cauchy distribution as the prior on the fixed effects ($r = 0.5$). Interaction BF s were calculated by comparing the full model against the main-effects-only model ($BF_{\text{interaction}} = BF_{\text{full}}/BF_{\text{main}}$). For post-hoc comparisons, we used ‘ttestBF’ with a medium Cauchy prior ($r = 0.707$). BF s are used to interpret the strength of evidence: BF values greater than 1 favour H_1 , while values less than 1 favour H_0 .

Adopting the classification system proposed by Wetzels and Wagenmakers (2012), evidence strength is interpreted as being *ambiguous* (or inconclusive; BF_{10} between 1 and 3 for H_1 , or between 1 and 1/3 for H_0), *substantial* (BF_{10} between 3 and 10 for H_1 , or between 1/3 or 1/10 for H_0), *strong* (BF_{10} between 10 and 30 for H_1 , or between 1/10 or 1/30 for H_0), *very strong* (BF_{10} between 30 and 100 for H_1 , or between 1/30 or 1/100 for H_0), or *decisive* (BF_{10} greater than 100 for H_1 , or less than 1/100 for H_0).

Transparency and Openness

This study was not preregistered. The data collection was conducted online from 23/03/2021 to 21/04/2021. The data and analytic code necessary to reproduce the reported results are available on the Open Science Framework (OSF) at:

https://osf.io/pwk6j/overview?view_only=36ddac26cdb2401ba94649895475fc35. A statement

outlining the generality of the findings is included at the end of the Discussion.

Results

Counter-Strike Expertise

Correlations

First, we examined the zero-order correlations between Counter-Strike expertise measures, which are reported in Table S2 of the Supplemental Materials. All four key Counter-Strike expertise measures were positively correlated. Total playtime was positively correlated with weekly playtime, $r(228) = .33, p < .001, 95\% \text{ CI } [.21, .44]$, self-rated expertise, $r(228) = .37, p < .001, 95\% \text{ CI } [.25, .48]$, and current ranking, $r(228) = .64, p < .001, 95\% \text{ CI } [.56, .71]$. Weekly playtime was also positively correlated with self-rated expertise, $r(228) = .34, p < .001, 95\% \text{ CI } [.22, .45]$, and current ranking,

$r(228) = .36, p < .001, 95\% \text{ CI } [.24, .47]$. Finally, self-rated expertise showed a strong positive correlation with current ranking, $r(228) = .64, p < .001, 95\% \text{ CI } [.56, .71]$.

K-Means Cluster Analysis

Next, we ran a series of *k*-means cluster analyses to group participants by their similarity on the four key Counter-Strike expertise measures. A consensus-based algorithm using 29 methods suggested that the optimal number of clusters was $k = 2$ (supported by 8 methods), $k = 3$ (supported by 5 methods), or $k = 4$ (supported by 5 methods; see Figure S5 in the Supplemental Materials). However, while the $k = 2$ and $k = 3$ solutions grouped participants into broader expertise levels, they failed to capture meaningful distinctions. For example, the $k = 2$ solution categorised participants into Novice ($n = 139$) and Skilled ($n = 91$) players, but the Skilled group included individuals with total playtime ranging from 150 to 13,000 hours, rendering this classification too broad. Hence, we chose $k = 4$, which provided a more refined differentiation of expertise, meaning that clusters showed clearer separation in the means of the four expertise measures along plausible ranges.

The $k = 4$ solution was verified via PCA analysis, where the first two components accounted for 78% of the total variance. PC1 (59%) captured the shared variance across all four measures (loadings > 0.70 for all variables). Visual inspection of the PCA biplot confirmed that the four clusters occupied distinct regions of the feature space. Cluster stability was assessed using bootstrapping, with resulting mean Jaccard similarity indices demonstrating high stability for the Novice (0.91), Skilled (0.82), and Expert (0.82) clusters, while the Emerging cluster (0.59) showed moderate stability. Furthermore, the generalisability of the cluster rules was confirmed with an 80/20 split-half validation. The model trained on the 80% training set successfully predicted memberships in the 20% hold-out set with a mean silhouette coefficient (0.34) that was consistent with the full-sample silhouette (0.36). The cluster silhouette coefficient plot for $k = 4$ showed positive silhouette coefficients for most participants ($n = 223$), with an average value of 0.36, indicating a reasonable fit (see Figure S6 in the Supplemental Materials). We also performed sensitivity analyses for the *k*-means clustering and all subsequent analyses without the participants with negative silhouettes ($n =$

7; see Figures S7-8 in the Supplemental Materials). As the conclusions remained the same, we chose to include all participants in the analyses reported here (alternative $k = 2$ and $k = 3$ solutions are reported in Figures S9-12 in the Supplemental Materials). Finally, a series of one-way ANOVAs confirmed that the four clusters differed in total hours of playtime, weekly hours of playtime, self-rated expertise, and current ranking (all $ps < .001$). Taken together, these results indicate that the four-cluster solution is robust and stable.

Based on mean values across four key measures of expertise, we labelled the four clusters as *Novice* ($n = 77$), *Emerging* ($n = 21$), *Skilled* ($n = 98$), and *Expert* ($n = 34$) players. Table 2 lists the sample characteristics, including the four primary Counter-Strike expertise measures for the full sample and the clusters. Figure 5 presents scatterplots of cluster points and means, and Table 3 provides descriptive statistics for cognitive measures across the full sample and the clusters (see Table S4 in the Supplemental Materials for descriptive statistics for other expertise variables).

Table 2

Demographic and Primary Counter-Strike Play Characteristics of the Full Sample and Clusters

Variable	Full Sample	Cluster			
		Novice	Skilled	Emerging	Expert
Age (years)	21.94 (4.72)	21.28 (4.82)	23.80 (4.69)	18.10 (2.69)	20.38 (3.02)
Gender (m/w/n/p)	206/21/1/2	70/6/0/1	81/15/1/1	21/0/0/0	34/0/0/0
Total playtime (hours)	1572.01 (1944.39)	623.19 (537.97)	990.01 (860.83)	1512.88 (972.36)	5434.88 (2082.08)
Weekly playtime (hours)	20.29 (15.74)	10.20 (7.58)	17.19 (7.93)	55.33 (12.36)	30.41 (12.54)
Self-rated expertise	50.70 (23.66)	26.06 (12.37)	63.11 (15.47)	49.14 (18.00)	71.65 (17.50)
Current ranking	12.00 (4.70)	7.69 (2.83)	13.30 (2.96)	11.57 (5.18)	18.29 (1.77)

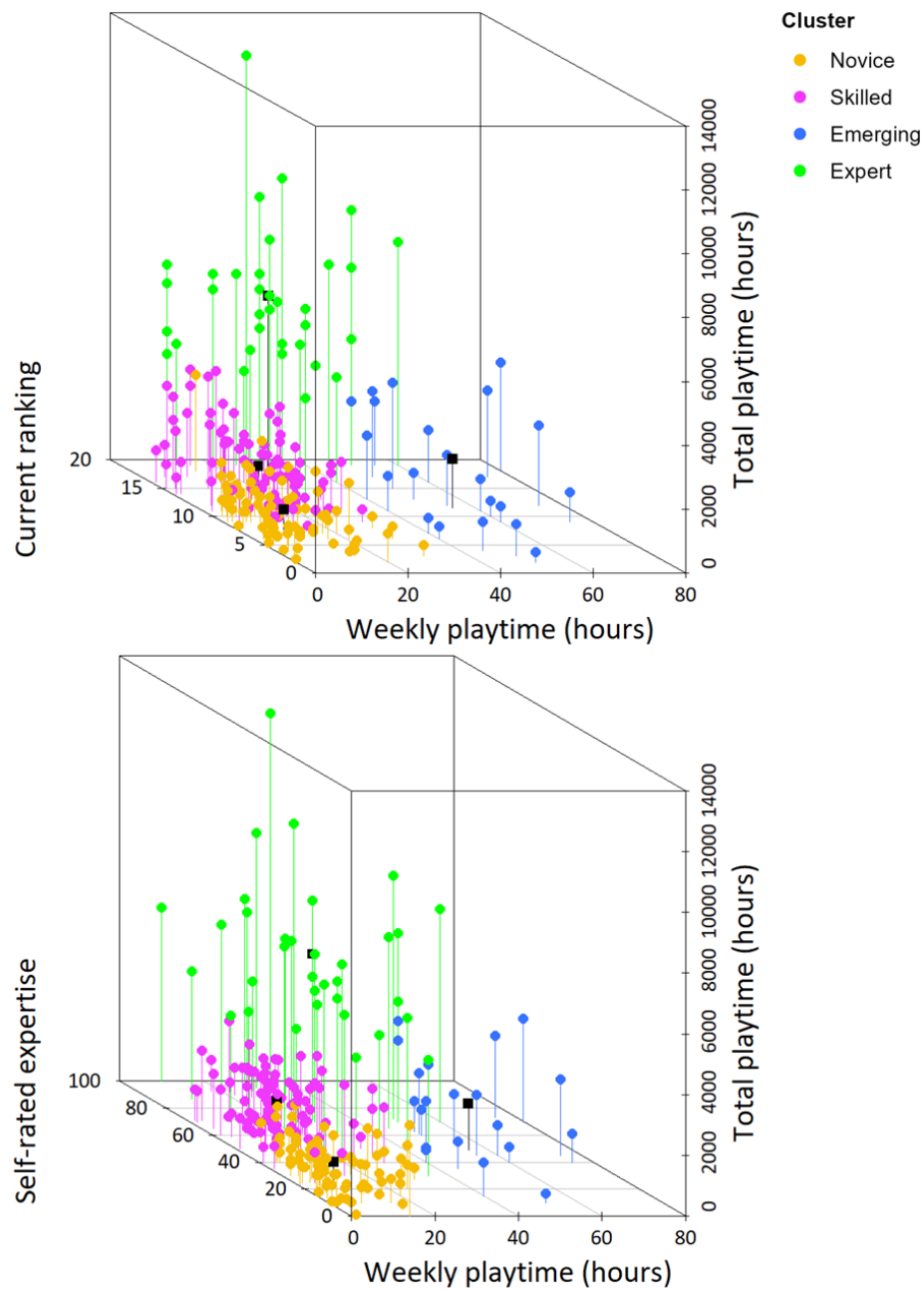
Note. Values given are overall means with between-subjects standard deviations, computed across

individual participant means, in parentheses. Full sample $N = 230$; Novice $n = 77$; Skilled $n = 98$;

Emerging $n = 21$; Expert $n = 34$. Three participants preferred not to disclose their age (one each of

the Novice, Skilled, and Emerging clusters). Gender m = men; w = women; n = non-binary; p =

preferred not to disclose.

Figure 5*Scatter Plots of Expertise Measures for Four Clusters Solution*

Note. Black squares represent means for the respective cluster.

Table 3*Descriptive Statistics of Cognitive Performance for the Full Sample and Clusters*

Variable (condition)	Full Sample	Cluster			
		Novice	Skilled	Emerging	Expert
Reaction time (ms)					
Single-rule	566.42 (108.02)	608.77 (118.31)	545.64 (97.29)	576.91 (93.33)	523.90 (90.71)
Repetition	968.75 (199.05)	1023.00 (232.49)	944.45 (180.68)	961.90 (172.59)	920.15 (159.25)
Switch	1147.49 (247.62)	1225.43 (276.71)	1080.26 (221.54)	1174.78 (241.57)	1147.87 (203.57)
Accuracy					
Single-rule	.95 (.04)	.95 (.04)	.94 (.04)	.93 (.07)	.95 (.06)
Repetition	.95 (.05)	.95 (.06)	.96 (.05)	.95 (.05)	.96 (.04)
Switch	.92 (.06)	.91 (.07)	.92 (.05)	.91 (.06)	.95 (.04)
Drift rate					
Single-rule	2.77 (0.85)	2.76 (1.02)	2.75 (0.68)	2.45 (0.61)	3.02 (0.97)
Repetition	2.44 (1.13)	2.24 (1.00)	2.62 (1.26)	2.07 (0.65)	2.64 (1.18)
Switch	1.73 (0.76)	1.65 (0.78)	1.73 (0.63)	1.47 (0.47)	2.10 (1.04)
Boundary separation					
Single-rule	1.68 (0.69)	1.80 (0.65)	1.50 (0.38)	1.68 (0.52)	1.95 (1.23)
Repetition	3.05 (1.87)	3.07 (1.72)	3.08 (2.06)	2.61 (1.28)	3.19 (1.93)
Switch	2.57 (1.67)	2.75 (1.88)	2.31 (1.40)	2.31 (0.91)	3.05 (2.07)
Non-decision time (ms)					
Single-rule	278.91 (75.86)	296.39 (77.72)	288.65 (60.87)	267.39 (50.77)	218.32 (93.30)
Repetition	383.75 (165.06)	383.63 (173.55)	399.60 (154.94)	373.87 (173.79)	344.44 (168.61)
Switch	490.38 (156.08)	498.15 (171.91)	498.79 (142.28)	480.92 (129.89)	454.36 (171.78)

Note. Values given are overall means with between-subjects standard deviations, computed across

individual participant means, in parentheses. Full sample $N = 230$; Novice $n = 77$; Skilled $n = 98$;

Emerging $n = 21$; Expert $n = 34$.

The cluster solution was derived from four Counter-Strike expertise variables: total playtime, weekly playtime, self-rated expertise, and current rank. While it is expected that the clusters would be distinct from one another, it was not guaranteed that every variable would significantly differ between the groups; some measures might prove to be more sensitive to group differences than others. Therefore, we conducted Kruskal-Wallis tests to examine the degree to which each expertise

variable varied significantly across the four clusters (see Supplemental Materials). The results confirmed a strong association between Counter-Strike expertise and cluster group membership. Participants classified as Experts consistently exhibited the highest levels of performance across all expertise measures, whereas Novice players demonstrated the lowest levels, supporting the validity of the clustering solution.

Effects of Expertise on Cognitive Performance

We examined the main effects of condition (single-rule, repetition and switch) and cluster (Novice, Skilled, Emerging and Expert), as well as their interaction, on RTs and accuracies. Figure 6 illustrates the average RTs of participants for each cluster and condition. Table 4 presents the main and interaction effects results for RT and accuracy. Table S5 in the Supplementary Materials lists all pairwise comparisons for RT and accuracy for conditions and clusters, and their interactions. Results of assumption checks (Levene's test and Mauchly's test) are reported in Tables S6 and S7 in the Supplementary Materials. Levene's test assumptions were met for RT and accuracy, but Mauchly's test assumptions were violated for RT, $\chi^2 = 0.715$, $p < .001$ and accuracy, $\chi^2 = 0.818$, $p < .001$. Therefore, Greenhouse-Geisser corrected degrees of freedom are reported.

Table 4

Mixed ANOVA and Bayesian Factor Analysis Results for Reaction Time and Accuracy

Effect	<i>df</i>	<i>F</i>	<i>p</i>	η_p^2	90% CI	<i>BF</i> ₁₀
Reaction Time						
Condition	1.56, 3351.75	1351.65	< .001	.89	.88, .90	> 1000
Cluster	3, 226	5.70	< .001	.07	.02, .12	52.41
Condition x cluster	4.67, 351.75	2.40	.040	.03	.01, .06	1/1.59
Accuracy						
Condition	1.69, 382.56	27.21	< .001	.17	.12, .22	> 1000
Cluster	3, 226	1.51	.214	.02	.00, .05	1/7.39
Condition x cluster	5.08, 382.56	2.01	.076	.03	.00, .04	1/3.45

Note. *p*-values of less than .05 are considered statistically significant and are printed in bold. *BF*₁₀ =

Bayes factor in favour of the alternative hypothesis. Degrees of freedom for condition and the condition x cluster interaction were adjusted using Greenhouse-Geisser corrections.

For RTs, there was a significant main effect of condition, which was supported by decisive Bayesian evidence, $p < .001$, $BF_{10} > 1000$. As expected, pairwise comparisons confirmed significantly longer RTs in switch trials ($M = 1147.49$ ms, $SD = 247.62$) relative to repetition trials ($M = 968.75$ ms, $SD = 199.05$), and significantly longer RTs in repetition relative to single-rule trials ($M = 566.42$ ms, $SD = 108.02$), $ps < .001$, $BF_{10s} > 1000$, $ds \geq 0.82$. The main effect of cluster was also significant, $p < .001$, supported by strong evidence, $BF_{10} = 52.41$. On average across the conditions, Novices were relatively slower ($M = 952.40$ ms, $SD = 337.56$) than Skilled ($M = 856.78$ ms, $SD = 286.09$), Emerging ($M = 904.53$ ms, $SD = 305.70$), and Expert players ($M = 863.97$ ms, $SD = 302.72$), with the comparison between Novice and Skilled players remaining significant after Bonferroni correction, $p = .013$, $BF_{10} = 10.22$, $d = 0.27$, 95% CI [0.10, 0.45].

Although the Greenhouse-Geisser corrected interaction between condition and cluster was significant, $p = .040$, the Bayesian evidence was ambiguous and in favour of the null hypothesis, $BF_{10} = 1/1.59$, reflecting only weak evidence associated with this effect. Bonferroni-corrected pairwise comparisons between expertise groups for each condition revealed that, in single-rule trials, Novice players were significantly slower ($M = 608.77$ ms, $SD = 118.31$) than Skilled players ($M = 545.64$ ms, $SD = 97.29$), $p < .001$, $BF_{10} = 249.85$, $d = 0.61$, 95% CI [0.31, 0.92], and Expert players ($M = 523.90$ ms, $SD = 90.71$), $p < .001$, $BF_{10} = 176.55$, $d = 0.82$ [0.40, 1.23].¹ In switch trials, Novice players were also significantly slower ($M = 1225.43$ ms, $SD = 276.71$) than Skilled players ($M = 1080.26$ ms, $SD = 221.54$), $p = .002$, $BF_{10} = 51.60$, $d = 0.54$ [0.24, 0.85]. No other pairwise comparisons survived Bonferroni correction, $ps \geq .124$.

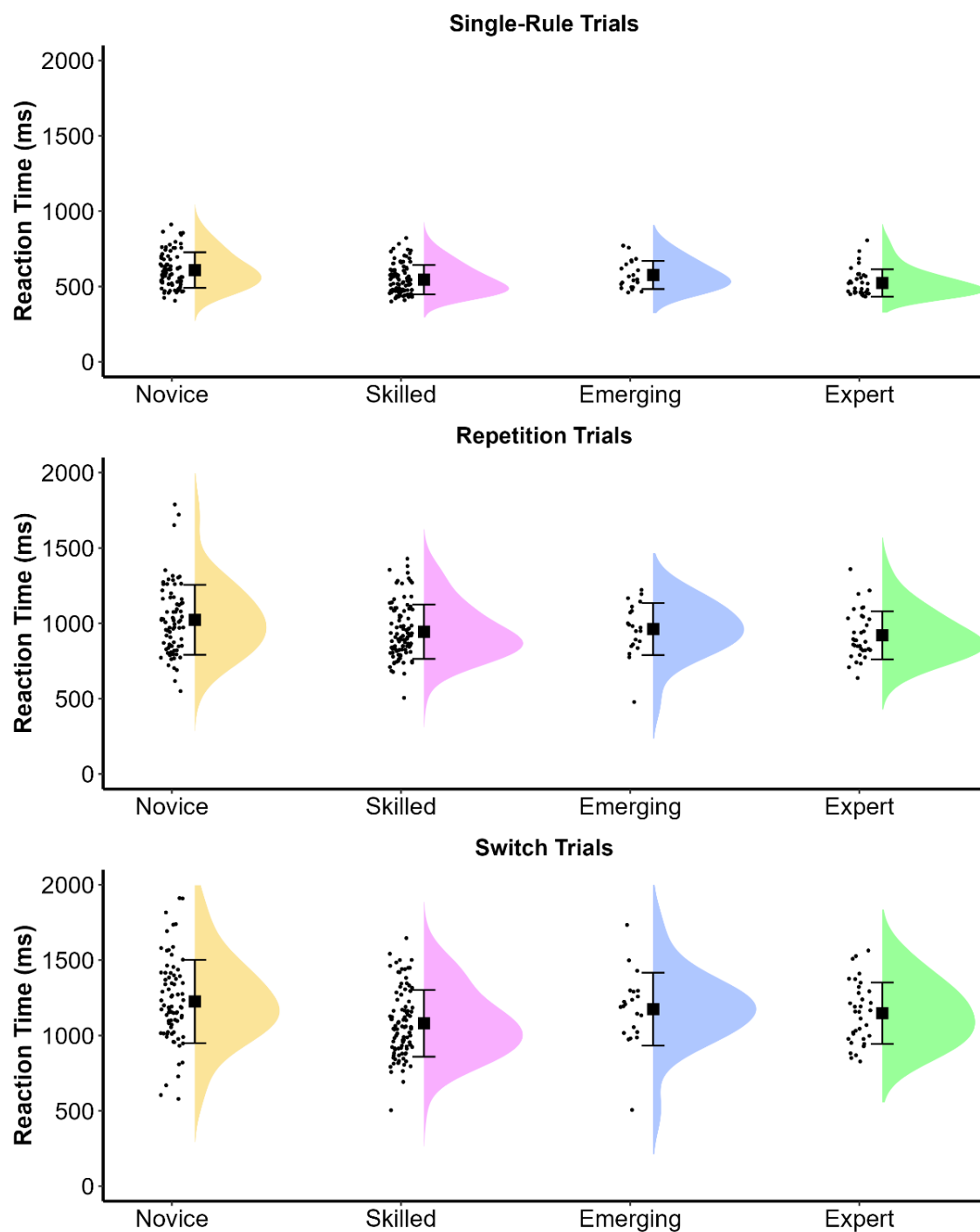
For accuracy, there was a significant main effect of condition, which was supported by decisive Bayesian evidence, $p < .001$, $BF_{10} > 1000$. Consistent with the RT results, accuracies were

¹ Because RTs in single-rule trials were significantly shorter for the colour than the shape task ($M_{diff} = 101.98$ ms), $F(1, 226) = 321.59$, $p < .001$, $\eta_p^2 = .59$, 95% CI [0.52, 1.00], $BF_{10} = 6.15$, we conducted sensitivity analyses testing the effects of expertise separately for each task. These analyses yielded the same pattern of results (for details, see Tables S10-12 in the Supplemental Materials).

higher in single-rule ($M = .95$, $SD = .05$) and repetition trials ($M = .95$, $SD = .04$) than in switch trials ($M = .92$, $SD = .06$), with the latter difference reaching significance, $p < .001$; $BF_{10} > 1000$, $d = 0.63$, 95% CI [0.44, 0.82]. However, there was no significant main effect of cluster, $p = .214$, with $BF_{10} = 1/7.39$. Similarly, the interaction effect was not significant, $p = .076$, $BF_{10} = 1/3.45$.²

Taken together, these findings suggest that Counter-Strike expertise is associated with differences in general processing speed, rather than in multitasking. The most robust performance differences emerged in the less attentionally demanding single-rule trials. Furthermore, the lack of differences in accuracy between clusters indicates that more experienced players maintained those faster responses without compromising accuracy, suggesting an absence of a speed-accuracy trade-off. To explore the decision-making processes underpinning these expertise-related differences, we next examined the parameter estimates from the DDM.

² Because accuracies in single-rule trials were significantly lower for the colour than the shape task ($M_{diff} = 0.02$), $F(1, 226) = 16.08$, $p < .001$, $\eta_p^2 = .07$, 95% CI [0.02, 1.00], $BF_{10} = 3.98$, we conducted sensitivity analyses testing the effects of expertise separately for each task. These analyses yielded the same pattern of results, except for the comparison between Emerging (colour: $M = .96$, $SD = .04$; shape: $M = .92$ ms, $SD = .09$) and Expert players (colour: $M = .95$, $SD = .09$; shape: $M = .96$ ms, $SD = .03$) reached significance for only the shape (Bonferroni-corrected $p = .048$), but not the colour task (Bonferroni-corrected $p = 1$). There is no theoretical reason to expect this effect. We can only speculate that it may be due to the relatively small number of Emerging players ($n = 21$), combined with random fluctuations from multiple testing (for details, see Tables S10-12 in the Supplemental Materials). Importantly, this difference does not impact the overall results because there was no difference in RTs between Emerging and Expert players.

Figure 6*Raincloud Plots of Reaction Time Across Clusters*

Note. Black squares represent means, and error bars represent standard deviations for the respective clusters.

Effects of Expertise on Drift-Diffusion Model Parameters

We examined the main effects of condition and cluster, as well as their interaction on the three parameters obtained from the DDM: drift rate (ν), boundary separation (α), and non-decision time (t_0). Figure 7 illustrates the DDM parameters across clusters and by conditions. Table 5 presents the main effect and interaction effect results for the DDM parameters. Pairwise comparisons for the DDM parameters are presented in Table S9 in the Supplemental Materials.

Table 5

Mixed ANOVA Results for Drift-Diffusion Model Parameters

Effect	<i>df</i>	<i>F</i>	<i>p</i>	η_p^2	90% CI	<i>BF</i> ₁₀
Drift rate						
Condition	1.84, 415.68	70.03	< .001	.13	.18, .29	> 1000
Cluster	3, 226	4.22	.006	.05	.01, .10	2.87
Condition x cluster	5.52, 415.68	1.20	.308	.02	.00, .03	1/17.07
Boundary separation						
Condition	1.56, 351.59	34.15	< .001	.20	.08, .18	> 1000
Cluster	3, 226	2.45	.064	.03	.00, .07	1/4.14
Condition x cluster	4.67, 351.59	0.80	.544	.01	.00, .02	1/49.41
Non-decision time						
Condition	1.66, 374.40	118.92	< .001	.42	.28, .40	> 1000
Cluster	3, 226	3.51	.016	.04	.00, .09	1.14
Condition x cluster	4.97, 374.40	0.29	.917	.00	.00, .00	1/195.42

Note. *P*-values of less than .05 are considered statistically significant and are printed in bold. *BF*₁₀ =

Bayes factor in favour of the alternative hypothesis. Degrees of freedom for condition and the condition x cluster interaction are adjusted using Greenhouse-Geisser corrections.

For drift rate, there was a significant main effect of condition, which was supported by decisive Bayesian evidence, $p < .001$, $BF_{10} > 1000$, reflecting higher drift rates for single-rule trials ($M = 2.77$, $SD = 0.85$) than for repetition trials ($M = 2.44$, $SD = 1.13$) and switch trials ($M = 1.73$, $SD = 0.76$), $ps < .001$, $BF_{10s} \geq 194.59$, $ds \geq 0.32$. The main effect of cluster was also significant, $p = .006$, though supported by ambiguous evidence, $BF_{10} = 2.87$. On average across conditions, Experts showed higher drift rates ($M = 2.58$, $SD = 1.12$) compared to Emerging ($M = 1.99$, $SD = 0.70$), Skilled ($M = 2.37$, $SD = 1.01$), and Novice players ($M = 2.22$, $SD = 1.04$). Bonferroni-corrected pairwise

comparisons rendered these differences significant between Experts and Emerging players, $p = .002$, $BF_{10} = 92.39$, $d = -0.60$, 95% CI [-0.92, -0.28], and between Experts and Novices, $p = .014$, $BF_{10} = 7.01$, $d = -0.54$ [-0.58, -0.11]. None of the other pairwise comparisons survived Bonferroni correction, $ps \geq .051$. There was no significant interaction between condition and cluster, $p = .308$, $BF_{10} = 1/17.07$.

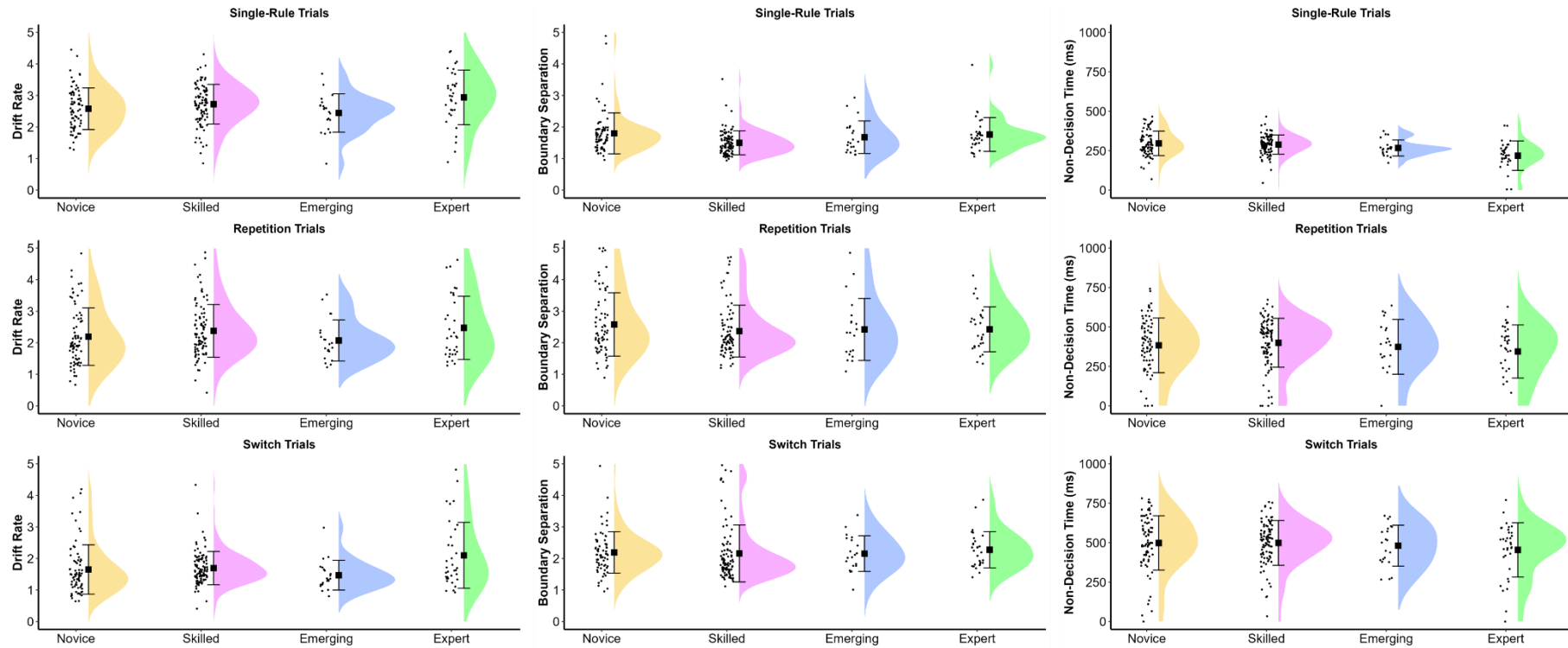
For boundary separation, we found a significant main effect of condition, which was supported by decisive Bayesian evidence, $p < .001$, $BF_{10} > 1000$. Participants showed narrower response boundaries in single-rule trials ($M = 1.68$, $SD = 0.69$) compared to repetition ($M = 3.05$, $SD = 1.87$) trials, $p < .001$, $BF_{10} > 1000$, $d = 0.97$, 95% CI [0.78, 1.16]. Repetition trials were also associated with significantly wider boundary separations than switch trials ($M = 2.57$, $SD = 1.67$), $p = .008$, $BF_{10} = 6.15$, $d = 0.27$ [0.09, 0.46]. These differences in boundary separation—which is set prior to evidence accumulation—may reflect adjustments in response caution based on the 150-ms task cue. However, there was no significant main effect of cluster, $p = .064$, $BF_{10} = 1/4.14$, nor an interaction effect $p = .544$, $BF_{10} = 1/49.41$.

For non-decision time, we found a significant main effect of condition, which was supported by decisive Bayesian evidence, $p < .001$, $BF_{10} > 1000$. Non-decision time was shortest for single-rule trials ($M = 278.91$ ms, $SD = 75.86$), followed by repetition trials ($M = 383.75$ ms, $SD = 165.06$), and switch trials ($M = 490.38$ ms, $SD = 156.08$), $ps < .001$, $BF_{10s} > 1000$, $ds \geq 0.66$. The main effect of the cluster was also significant, $p = .016$, but with only ambiguous evidence, $BF_{10} = 1.14$, which is reflected by a wide confidence interval around the effect size, $\eta_p^2 = .04$, 90% CI [.00, .09]. On average across conditions, Experts showed shorter non-decision times ($M = 339.04$ ms, $SD = 176.54$) than Emerging ($M = 374.06$ ms, $SD = 154.07$), Skilled ($M = 395.68$ ms, $SD = 152.54$), and Novice players ($M = 392.72$ ms, $SD = 169.02$). The only differences that remained significant after Bonferroni corrections were between Experts and Skilled players, $p = .015$, $BF_{10} = 11.98$, $d = 0.36$, 95% CI [0.13, 0.58], and Expert and Novice players, $p = .033$, $BF_{10} = 3.45$, $d = 0.31$, 95% CI [0.08, 0.55]. The interaction effect was not significant, $p = .917$, $BF_{10} = 1/188.26$.

In summary, the DDM analyses revealed that expertise-related performance differences are driven by differences in both evidence accumulation and the non-decision component of the decision-making process, but not due to differences in speed-accuracy trade-off. The absence of interactions with the trial condition further supports the behavioural results, suggesting that the effects are not specific to the attentional demands posed by shifting between mental sets.

Figure 7

Raincloud Plots of Drift Rates, Boundary Separations and Non-Decision Times Across Clusters



Note. Black squares represent means, and error bars represent standard deviations for the respective clusters.

Discussion

This study investigated multitasking, processing speed and decision-making performance in a large and diverse sample of FPS players. We employed a data-driven *k*-means clustering approach to classify Counter-Strike players into four expertise groups (Novice, Skilled, Emerging, and Expert players), combining objective and subjective metrics of FPS expertise. Performance on a task-switching paradigm revealed that FPS expertise was associated with faster RTs, particularly under conditions of low attentional demand (i.e., single-rule trials), and without compromising accuracy. Subsequent DDM analysis revealed that these differences in general processing speed were driven by more efficient evidence accumulation processes and shorter non-decision times for players with higher levels of expertise. Together, these findings suggest that FPS expertise relates to a general processing speed advantage driven by greater decision-making and perceptual-motor efficiency.

Expertise Advantage in Processing Speed, Not Multitasking

Our findings provide a resolution to a key theoretical ambiguity in the literature: whether the previously observed performance advantage of FPS players in cognitive tasks reflects differences in multitasking or simply in general processing speed. Our results strongly support the latter possibility. By examining the interaction between expertise and task conditions in a task-switching paradigm, we found no evidence for players with more expertise performing better, specifically in multitasking conditions. Instead, if anything, the association between expertise and speed was more pronounced under conditions with low attentional control demands. Therefore, these results provide compelling evidence that FPS expertise is associated with a general processing speed advantage. These findings are consistent with previous literature demonstrating advantages in processing speed performance in FPS players (Dale & Green, 2017; Dye et al., 2009; Karle et al., 2010). Furthermore, these findings lay the groundwork for future intervention research to determine whether FPS game-based training can be used as a tool to enhance general processing speed. For instance, in older adults experiencing age-related cognitive decline, processing speed training has been suggested to be beneficial for quality of life and maintaining independence (Tennstedt & Unverzagt, 2014).

Decision-Making and Perceptual-Motor Efficiency

DDM analysis further elucidated the cognitive mechanisms underlying the differences in processing speed performance between less and more experienced FPS players. We found that FPS expertise related to faster evidence accumulation and non-decision times. The rate of evidence accumulation has previously been shown to be strongly related to general intelligence (Lerche et al., 2020; Schmiedek et al., 2007) and to be a relatively stable trait (Schubert et al., 2016). Non-decision time is a composite measure, which includes stimulus encoding, motor response execution and task-set reconfiguration. Our analysis does not allow for isolating whether the observed differences are purely perceptual, purely motor, or a combination of both. Nonetheless, the absence of a significant interaction between expertise and task condition allows us to rule out expertise-related differences in task-set reconfiguration—and, by extension, multitasking-specific advantages—as the primary driver of this expertise effect: Had a multitasking advantage been the defining characteristic of FPS expertise, we would have expected shorter non-decision times specifically in switch trials for Expert players. Instead, because the expertise advantage occurred uniformly across both repetition and switch trials, the results suggest that the effect was driven by greater perceptual-motor efficiency regardless of attentional control demands. Because perceptual and motor components remain entangled in the total non-decision time, future research is needed to determine whether the association between expertise levels and non-decision time is driven by better encoding, motor execution, or both.

Our findings complement a growing body of neuroimaging research indicating better decision-making and perceptual-motor efficiency in action video game players. Previous studies, for example, have identified structural and functional advantages in brain regions associated with sensorimotor control in action video game players (Giboin et al., 2021; Granek et al., 2010; Jordan & Dhamala, 2022; Lin et al., 2025; Morin-Moncet et al., 2016). Furthermore, while Gozli et al. (2014) found no general behavioural advantage in sensorimotor control in video game players, they demonstrated that players showed a faster rate of improvement in sensorimotor learning tasks with

a consistent, predictable structure. The processing speed advantage we observed in trials requiring repeated responses to a single set of rules can be considered analogous to this type of predictable task, suggesting that the shorter non-decision times in Expert players in the present study may reflect this learned efficiency at the perceptual-motor level.

Pre-Existing Advantages, Experience-Based Gains, or Both?

While our findings establish associations between FPS gameplay and cognitive performance, they cannot reveal any causal relationship due to the cross-sectional nature of the present study. Specifically, the present data cannot distinguish between the possibilities (1) that people with better baseline drift rates and faster non-decision times self-select to play FPS games more frequently and, thus, develop stronger FPS expertise, (2) that FPS play acts as cognitive training and, thereby, enhances performance in these parameters, or (3) a combination of those possibilities.

DDM parameters have indeed been shown to be relatively stable over time in the absence of interventions (Schubert et al., 2016). Yet, there is some evidence from training studies that speaks for the possibility that experience may yield improvements. For example, Green et al. (2010) administered 50 hr of video-game training, which resulted in measurable improvements of drift rates and changes in boundary separation in a perceptual discrimination task. Similarly, Reinhartz et al. (2023) observed improvements in drift rate after 20 hr of perceptual discrimination training. These changes were accompanied by reductions in non-decision time and changes in boundary separation. Whereas non-decision times and boundary separation changed rapidly at the beginning of the intervention, drift rates improved more slowly and steadily over the course of the training period. Importantly, though, the amount of training in Green et al.'s (2010) and Reinhartz et al.'s (2023) is not comparable to even the experience of the Novice players in the present study, who on average had already accumulated a playtime of on average 623 hr. Moreover, post hoc comparisons between the expertise groups indicated players with the highest level of expertise – with on average 5435 hr of play experience – differed from all other groups, but the other groups did not differ from each other. This may indicate a qualitative, rather than a quantitative, difference between the Experts and all

other groups, which in turn suggests that these may be pre-existing cognitive differences that are beneficial for becoming an Expert player, rather than practice benefits resulting from playing the game. Indeed, given the wider literature on cognitive enhancement and skill acquisition (e.g., for an overview, see von Bastian et al., 2022), the third possibility may be most likely, whereby people with higher baseline cognitive performance would be more likely to play more frequently and become experts in the game, and the resulting sustained practice of dealing with the cognitive demands of the game in turn also improving their cognitive performance further (Vaci et al., 2019).

While the present findings are correlational, they may still inform future research exploring the potential of FPS games to serve as tools for training decision-making skills in applied settings. FPS gameplay requires the rapid detection and response to dynamic stimuli under significant time pressure. These skills are critical not only in gaming, but also in high-stakes real-world environments that place similar demands on decision-making and perceptual-motor skills – for example, driving and air traffic control, which require individuals to quickly process a stream of complex and changing information, and to execute precise, time-sensitive actions. The observed performance advantages among Expert FPS players raise the possibility that sustained engagement with such games may offer cognitive benefits. Such longitudinal research would help determine whether FPS gameplay improves decision-making and perceptual-motor abilities, or whether individuals with better baseline abilities are more likely to become Expert players. Preliminary intervention studies have shown a benefit of FPS gameplay to the perceptual-motor system during lane-keeping and visuomotor control tasks (Li et al., 2016), suggesting that FPS games could be a powerful intervention for targeting perceptual-motor abilities.

Limitations and Future Directions

While this study offers valuable insights into the cognitive correlates of FPS expertise, several limitations must be acknowledged. First, while the present sample is larger than in most other video gaming studies, the majority of participants were men. While this reflects the Counter-Strike community, it limits the generalisability of our findings across genders. In contrast, the present

sample had a relatively wide age range (16 to 35 years), during which cognitive skills are still developing. However, including age as a covariate did not affect the findings and, therefore, we are confident that differences observed in more experienced clusters were not a byproduct of age (see Table S7 in the Supplementary Materials). Furthermore, we did not collect data on socioeconomic status (SES), education, or general intelligence. Previous research suggests that educational attainment and general intelligence were related to video game expertise (Quiroga et al., 2015; Sala et al., 2018). Without controlling for these factors, we cannot rule out the possibility that our findings are also influenced by these variables. Future research should include and report those variables to better understand how they contribute to the relation between FPS expertise and cognitive performance.

Second, we measured processing speed and multitasking using one particular paradigm; consequently, our findings cannot be generalised to attentional capacity more broadly. For example, FPS players often show greater accuracy in tracking multiple moving targets (Bediou et al., 2018; Green & Bavelier, 2006). These behavioural advantages are often underpinned by a more efficient recruitment of top-down attentional control networks and a greater degree of automaticity in task execution, as evidenced by neuroimaging and electrophysiological studies (Bavelier et al., 2012; Föcker et al., 2018; 2019). Using a broader battery of tasks, possibly combined with cognitive modelling and neuroimaging techniques, would be a valuable way to reconcile these two strands of evidence.

Third, some concerns regarding the assessment of Counter-Strike expertise remain. While 3 of the 4 expertise measures used in this study (i.e., total playtime, weekly playtime and current ranking) were objective metrics automatically logged and made accessible through Steam (the game platform) – representing a key strength of the present study over previous research that relied entirely on self-rating scales – they were nevertheless ultimately obtained through participant report. Although participants were prompted to verify these metrics directly in their Steam profiles before submission, the manual entry still left the data susceptible to clerical inaccuracies (e.g., copy-paste or

transcription errors) and, potentially, intentional misreporting. Future research could enhance data accuracy by using third-party in-game metric-tracking platforms such as Leetify (www.leetify.com) or by extracting data directly from Steam.

Fourth, the online data collection method used in the present study introduces potential variability in hardware and environmental distraction, though a robust body of literature shows that online studies reliably replicate RT effects established in laboratory settings (Bridges et al., 2020; Germine et al., 2012). To mitigate technical variance, the experimental software used in the present study (Tatool Web, www.tatool-web.com) preloads stimuli to the local machine, which ensures performance is not impacted by internet latency. Furthermore, the online approach allowed for a large sample size, reflecting a wide range of expertise, which would be difficult to achieve through in-person data testing.

Fifth, our clustering method, while data-driven, resulted in two relatively small clusters for the Emerging ($n = 21$) and Expert ($n = 34$) clusters. The small sample size within these two clusters may have contributed to the significant heterogeneity of variance observed in drift rates for switch trials and non-decision time for single-rule trials. Further statistical support for a degree of overlap between clusters is provided by our silhouette coefficient of 0.36, which is considered fair but falls short of indicating highly distinct clusters. Additionally, our data collection occurred during the coronavirus disease (COVID-19) pandemic, a period of unusually high video game engagement (DiFrancisco-Donoghue et al., 2023). While participants' reported playtime and expertise gained are still valid, the intense nature of this gaming period may have created a unique participant profile that is not representative of the broader FPS player population. Specifically, the Emerging group, which was characterised by an exceptionally high weekly playtime, may be an artefact of this intense gaming period rather than a stable expertise level. Furthermore, this extreme engagement in the Emerging group may capture elements of problematic gaming during the COVID-19 pandemic rather than high-level skill acquisition (King et al., 2020). Future research should seek to replicate this study

in a post-pandemic context with a similarly sized sample to determine whether these expertise groups are a stable feature of the FPS player population.

To address the limitations of our clustering approach, studies should adopt more flexible techniques, such as Gaussian Mixture Models (GMM), which can accommodate varying cluster shapes (i.e., non-spherical), and assign data points (i.e., participants) to multiple clusters, providing a more nuanced classification. Additionally, our current clustering variables did not account for critical in-game performance factors, such as specific player roles, which may lead to distinct cognitive profiles. Incorporating these variables would likely provide a deeper understanding of the relationship between gaming expertise and cognitive mechanisms. For example, a player whose role demands rapid, high-risk engagements (e.g., a front-line player) may exhibit different DDM parameters compared to a player whose role requires patient, strategic positioning (e.g., a sniper). By including such context-specific variables, it will be possible to move beyond broad classifications and capture the specific cognitive demands of different aspects of FPS gameplay styles.

Finally, as discussed above, the present study does not allow for drawing conclusions about the causality of the associations between FPS experience and cognitive performance. To establish such causal relationships and their directionality, longitudinal studies are essential. For example, such a study could track a cohort of novice players over an extended period as their FPS expertise progresses, measuring changes in their perceptual-motor skills and DDM parameters. In conjunction with behavioural measures, neuroimaging techniques such as electroencephalography (EEG) or functional magnetic resonance imaging (fMRI) could provide a direct neural correlate for these decision-making and perceptual-motor efficiencies.

Constraints on Generality of Findings

The target population for the reported findings is players of FPS games, such as Counter-Strike, spanning the full spectrum of expertise from novices to professional esports athletes. While restricting the sample to this specific, fast-paced, dynamic and complex video game genre is a methodological strength of the study, the reported findings cannot be extended to players of less

perceptually demanding game genres (e.g., strategy games, puzzle games), which likely involve different cognitive correlates. The finding that expert performance is characterised by higher evidence-accumulation rates and perceptual-motor efficiency (reflected by higher drift rates and shorter non-decision times) is most applicable to tasks requiring rapid visual encoding, decision-making, and motor execution. Furthermore, due to the correlational design, we cannot ascertain if FPS training causes such cognitive benefits – only that expertise in FPS games is associated with this specific cognitive profile.

Conclusion

This study resolves a key ambiguity in the literature by demonstrating that expertise in decision-making under pressure, as observed in high-intensity FPS games, is associated with a general processing speed advantage rather than superior multitasking. This advantage is driven by more efficient decision-making and perceptual-motor abilities. By combining objective gameplay metrics with a data-driven clustering approach in a large and diverse sample of Counter-Strike players, we offer a robust methodology for examining the underlying components of cognitive performance in this unique population. While methods are correlational, these findings may inform future intervention research targeting processing speed, decision making and perceptual-motor skills in the context of FPS games. These findings also raise fundamental theoretical questions regarding the directionality of this relationship: do individuals with higher baseline cognitive abilities gravitate toward and excel in cognitively demanding activities like FPS games, or do the demands of these games actively shape performance over time? To establish a causal link and clarify this relationship, longitudinal and neuroimaging studies will be key to establishing how to harness the cognitive potential of FPS games as a promising and engaging tool for cognitive intervention.

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Eleanor R. A. Hyde: conceptualisation, data curation, formal analysis, investigation, methodology, project administration, resources, software, visualisation, writing—original draft, and writing—review and editing. Robert Schmidt: methodology, supervision, writing and editing. Daniel J. Carroll: supervision, writing and editing. Claudia C. von Bastian: conceptualisation, funding acquisition, methodology, project administration, resources, software, supervision, and writing—review and editing.