

# Associations Between Cognitive Performance and Extreme Expertise in Different Competitive eSports

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## Abstract

As video gaming and competitive eSports have garnered increased empirical attention, a knowledge gap persists concerning the cognitive underpinnings of performance in individual gaming genres. Indeed, just as is true of traditional sports, where different abilities underlie performance in, for instance, tennis versus wrestling, eSports players require distinguishable skills to perform well in any particular genre, and these genre-specific skill sets likely load upon unique cognitive constructs. The present study aimed to assess the relations between high-level expertise in two different eSports and performance on a number of cognitive assessments in an effort to isolate the cognitive processes that most directly support top-level competitive gaming performance in those eSports. Top-level experts of the Fighting and Rhythm game genres outperformed Non-video-game players (NVGPs) on measures of reaction time, paced motor timing, and sustained attention. Fighting Game Experts performed particularly well on a measure of sustained attention, while Rhythm Game Experts performed particularly well at paced motor timing. Interestingly though, the expert groups did not tend to differ dramatically from one another, suggesting either relations between the cognitive capacities and more general gaming expertise (rather than game specific expertise), or that the specific forms of expertise necessary are more shared across these game genres than anticipated. This work provides an initial look at the effects of video game expertise in fighting and rhythm games, as well as offering some explanation for how genre-specific expertise may interact with certain cognitive abilities.

## Keywords

eSports, video game expertise, cognition, genre specificity, reaction time

## Introduction

Within the broad research field centered on high-level expert performers, one major area of research has focused on correlations between the attainment of expert level status in the given domains of interest (e.g., particular musical instruments, chess, particular sports, etc. (Brown et al., 2015; Charness, 1992; Mann et al., 2007)) and a set of more primitive abilities involving cognition, perception, and motor

control. These associations are of interest both from a theoretical perspective as well as for practical applications. From a theoretical perspective, the observation of links between certain lower-level cognitive abilities and higher-order expertise can suggest that the complex tasks load upon those more primitive abilities (Bowman et al., 2018). In essence, by understanding the capacities wherein experts in

a domain differ from non-experts, researchers can then create models of skilled performance in the domain starting with its lowest level underpinnings. Meanwhile, in terms of practice, understanding the nature of these associations may provide a means of selection for potential experts. If a certain complex task heavily relies on reaction time, for instance, it may be that untrained individuals with especially fast reaction times may be more likely to attain greater levels of skill when trained on said task.

This general approach to examining the underpinnings of expertise has been explored in many domains such as professional sports. Meta-analyses on this topic have shown that more-skilled athletes exhibit a variety of enhanced perceptual capabilities, such as faster reaction times, better cue detection, and better attention maintenance (Mann et al., 2007; Voss et al., 2010). Critically, research has also assessed how these cognitive enhancements may differ by type of sport. For example, athletes who play what are sometimes labeled “interceptive sports,” such as tennis and baseball, have been seen to exhibit better visual clarity, reaction time, and contrast sensitivity, while athletes who compete in what have been labeled as more “strategic sports,” such as soccer and basketball, have been seen to exhibit enhanced spatial working memory (Burris et al., 2020). Other research in this same vein includes the finding that athletes who compete in sports emphasizing a horizontal distribution of attention (e.g., hockey) demonstrate greater horizontal breadth of attention than those who compete in sports demanding more vertical attention (e.g., volleyball), and vice versa (Hüttermann et al., 2014). In all, the existing literature on the relations between expert-athlete-status and cognitive performance generally support the notion that there are predictable links between high-level performance in particular sports and the cognitive abilities that are heavily/uniquely loaded upon in those sports.

More recently, video games is one particular domain of rising interest among those who study expertise. Like traditional sports, video games are complex task environments that can

place demand on a host of cognitive sub-systems (Bowman et al., 2018). In studies of the cognitive underpinnings of video games, much of the work to-date has categorized individuals based on their time spent playing video games, rather than on true measured “expertise.” In essence, this literature starts from the reasonable supposition that individuals tend to spend more time on tasks that they are good at (e.g., as would be predicted by any number of motivation frameworks such as Expectancy-Value theory [Wigfield & Eccles, 2000]) and thus time-spent playing video games can be used as a stand-in for skill level. Using this methodological framework, some consistent trends have emerged, particularly regarding a specific genre of games coined “action video games” (Green & Bavelier, 2003). This genre consists mainly of first- and third-person shooting games, such as *Call of Duty* and *Gears of War*. These games require the player to monitor a dynamically changing environment constantly, attending to threats, objectives, teammates, and other stimuli. This repetitive scanning of the gaming environment and rapid sifting through large amounts of visual input to select the most important targets of attention is thought to place a considerable cognitive load on the players, especially for constructs related to processing speed and visuospatial attention.

Consistent with this notion, myriad studies have found evidence for positive relations between the amount of time individuals spend engaged with action video games and their level of perceptual/cognitive skill (Feng et al., 2007; Li et al., 2009; Spence et al., 2009; for recent meta-analyses, see Bediou et al., 2018, 2023). Similar research has expanded into new gaming genres such as real-time strategy (RTS, e.g., *StarCraft*) and multiplayer online battle arena (MOBA, e.g., *League of Legends*), with researchers finding significant correlations between time spent playing these games and visual selective attention (Qiu et al., 2018), working memory (Yao et al., 2020), and multitasking ability (Chang et al., 2017).

Yet, while research utilizing the amount of time spent playing video games as a partial stand-in for skill comprises a rich and valuable

literature, it is nonetheless the case that the amount of time spent playing video games is likely to be, at best, an incomplete proxy for true expertise. Indeed, the literature on learning is rife with examples of significant individual differences in asymptotic abilities among individuals provided with the exact same amount of experience. As such, a second main area of research in this domain has sought to quantify skill level more directly within the video games themselves and use these quantifications of skill as the to-be-predicted measures. Finding a way to measure video game skill objectively is a complex undertaking and until recently was arguably somewhat practically infeasible. However, today there exists a burgeoning industry centered around the quantification of video game skill.

Spurred on by the inception of live broadcasting platforms such as Twitch and YouTube, the eSports industry, which pits skilled gamers against one another in competitions and tournaments, has grown from a niche, grassroots endeavor to an enterprise on the scope and scale of many traditional sports (Block & Haack, 2021; Reitman et al., 2020). Critically, for research endeavors, this has in turn created an infrastructure for measuring objective video game skill level directly through competition (for a comprehensive overview of eSports and its utility for cognitive research, see Phillips, 2023). Often taking inspiration from measures developed for more classic games (e.g., chess), a host of established methods now exists for quantifying skill, whether it be through tournament results, statistical rankings, Elo ratings, or global leaderboards.

And while Pedraza-Ramirez et al. (2020) point out that these metrics are not uniform across games and may be unreliable on their own for predicting underlying cognitive performance, they ultimately agree with Pluss et al. (2019) that the characteristics of the gaming environment may offer greater experimental control and ecological validity than even empirical research on traditional sports as they relate to specific cognitive processes. Consistent with these observations, multiple recent studies have utilized objective metrics of ability as a

primary criterion for delineating expert groups (Large et al., 2019; Toth et al., 2019). One common methodology is to utilize in-game match-making rating (MMR), a numerical system implemented in many competitive games to match players against similarly skilled opponents. For instance, Large et al. (2019) took this approach to categorize *League of Legends* players based on this quantitative representation of game performance, finding that higher levels of expertise were associated with enhanced speed of processing as well as attentional abilities. Similarly, Toth and colleagues (2019) used categorical in-game rankings for *Counter-Strike: Global Offensive* (e.g., Silver I, Gold Nova III, Global Elite) to classify skill levels for their participants who completed a color-word Stroop Task, finding that although the intended skill of cognitive inhibition did not differ among skill groups, elite level players did exhibit better performance when considering both accuracy and speed, as compared to both intermediate and novice level players.

Interestingly, one commonality across the video game expertise studies to date is that they have overwhelmingly focused on exceedingly complex game types (e.g., first-person shooters, third-person shooters, MOBAs, RTS games, etc.) that by their nature must necessarily involve a wide array of cognitive abilities that often involve team dynamics, etc. Here we sought to examine two genres that one might consider a priori more amenable to the examination of matches between certain cognitive capacities and expert-level performance—namely fighting games and music games.

In fighting games, generally one player competes against another to deplete their opponent's health by using various attacks and special moves. In many games, sequences of different attacks can be strung together as "combos." Some exemplars of this genre include *Street Fighter*, *Super Smash Bros.*, and *Mortal Kombat*. Fighting games have thus far comprised a relatively moderate share of total eSports popularity, although world tournaments for fighting games such as the EVO Championship Series bring thousands of players

to Las Vegas every year, competing for hundreds of thousands of dollars in prize money (*Esports Earnings*, 2019). Similarly, recent world circuits such as the 2023 Capcom Cup for the newly released game *Street Fighter 6* have amassed prize pools of more than two million dollars, with one million dollars to be awarded to the grand champion alone (*Capcom*, 2023). Compared to other video games, fighting games provide an opportunity to focus more heavily on the individual player versus player dynamic. Advanced competitors will not only have achieved mastery of the underlying game mechanics but will also excel in predicting their opponent's move choices and be able to preempt it with their own counterattack or defensive maneuver. Without having to rely on random elements or the actions of teammates, a competitor's skill relies fundamentally on their own cognitive processes. Although little research exists to date on cognitive function and fighting games, the research that has been conducted is consistent with the links that would have been a priori expected. For instance, one study examined top-level players of the *Guilty Gear* fighting game, finding that these world-class experts exhibited greater working memory performance, and even showed an increase in gray-matter volume in the right posterior parietal cortex, compared to non-experts (Tanaka et al., 2013).

In music/rhythm games meanwhile, players generally follow along with a predetermined sequence of button inputs, or notes, for any given song. Some classic examples of these games include *Guitar Hero*, *Rock Band*, *osu!*, and *Dance Dance Revolution*. Rhythm games are typically single-player rather than multi-player, but massive competitive communities still exist with thousands of players vying to achieve the highest scores on the leaderboards. These games are particularly amenable to quantification of skill since the fundamental goals of the games directly offer such measures (e.g., number of notes successfully played; noting though that total points often involves additional calculations related to multipliers for streaks of successful notes, etc.). Research on the cognitive associations with high-level

rhythm game expertise is functionally nonexistent, although rhythm games themselves have been utilized as a potential intervention in Parkinson's disease patients (Dalla Bella, 2022), and a custom rhythm game has been developed to help train rhythmic motion skills for the traditional sport of skiing (Katsuyama et al., 2022). We do, however, have access to a potentially useful analogue of studies examining expert level musicians and cognition. Studies on the associations between musical expertise and cognition have found that experts outperform non-experts, particularly on auditory-based cognitive tasks, such as those measuring auditory attention (Bianco et al., 2022; Carey et al., 2014), working memory (Nie et al., 2022), cognitive flexibility (Slama et al., 2017), and other facets of auditory cognition (see Kraus & Chandrasekaran, 2010, for a review). Some further work suggests that expert musicians display faster visual information processing, but only when stimuli are domain specific (i.e., reading musical scores) (Jónsson et al., 2022). While these results do not guarantee similar findings for expertise in rhythm video games, they offer a promising start and sufficient justification to choose this gaming genre for further study.

Finally, while these two genres have value in and of themselves with regard to assessing relations between cognitive skills and expertise, they together also make for an important contrast. Indeed, the vast majority of research in the video game space has either examined cognitive performance across levels of ability within a single game (e.g., across levels of skill in *League of Legends*) or has contrasted performance in experts/avid players against non-experts. Such research is important, as it does allow the assessment of skills that underpin skilled performance. However, such methods do not allow for the identification of predictors of game-specific versus game-general skill (i.e., whether there are some skills that are uniquely tapped by a given game rather than being important for skilled performance in all, or at least many different types, of video games).

Fighting games and music games make for an important contrast as both genres require

high levels of fine motor proficiency to execute complex sequences of button inputs properly. However, many other cognitive demands may be unique to each genre. In a fighting game, competitors must stay vigilant, ready to strike the very moment their opponent presents any opening or weakness. In a sense, this resembles true combat between trained martial artists. Additionally, fighting games generally require the player to choose their response to a given situation from a wide range of special moves, each of which may be the optimal response in only a few situations. Rhythm game players, on the other hand, are more like actual musicians, reciting a rehearsed sequence as perfectly as they can. There is much less variability in this environment as compared to that of a fighting game, and the inherent predictability of rhythm games may naturally limit the kinds of dynamic cognitive allocation that may be seen in fighting games. By comparing cognitive performance for players of both genres, we may find that any differences in performance could be related to the unique demands of each genre. We expect these differences to become more profound at the highest levels of skill, since the skill level demonstrates the level of engagement the players have with the cognitive demands of each game.

Here we offer a mixture of the types of approaches discussed above. In Experiment 1, fighting game players at all levels of skill were asked to complete a battery of cognitive tasks to assess relevant markers of cognitive performance, such as fluid intelligence, reaction time, and sustained attention. We hypothesized that participants with greater gaming expertise would tend to show better cognitive performance, particularly on tasks which test perceptual and motor abilities most relevant to competitive performance in the fighting game genre. Then in Experiment 2, we sought to directly contrast the performance seen in the highest-level expert fighting game players from Experiment 1, with a new set of experts from the music/rhythm game genre. Once again, we expected to find a general effect of expertise associated with greater cognitive performance, although we hypothesized that a divergence may

appear, where fighting game experts excel at tasks measuring constructs relevant to their gaming genre, while rhythm game experts may excel at different tasks, highlighting the intrinsic difference in game mechanics and cognitive loading present within each separate genre.

## Experiment 1: Fighting Game Novices vs Intermediates vs Experts

In this experiment, competitive video game players of the fighting game genre underwent a cognitive task battery to assess various metrics of cognitive function. Our main goal was to examine associations between competitive gaming skill and cognitive performance. To accomplish this, we recruited a diverse set of fighting game players with various skill levels, categorizing them into one of three groups: Novices, Intermediates, and Top-level Experts. Our strongest a priori hypothesis relates to reaction time as a metric for processing speed. We hypothesized that extremely fast processing speed may be integral to competitive video game performance, therefore we expected that Top-level Expert players would significantly outperform Intermediates and Novices on our reaction time tasks. Additionally, we hypothesized that working memory, sustained attention, and sequence learning are also at least somewhat vital to competitive fighting games, therefore we hypothesized that our Experts would perform significantly better on tasks measuring these constructs as well. Although some aspects of fluid intelligence, such as general problem solving, are surely taxed to some extent in these competitive games, we did not expect to see any significantly observable differences in intelligence among our expertise groups.

## Methods

All procedures were approved by the research ethics board at the University of Wisconsin-Madison. Study materials and preregistration can be found at <https://osf.io/zksqx/>.

## Participants

Competitive players of the fighting game genre were contacted for possible participation by the first author via email, direct messaging, and

recruitment posts made to Twitter, Reddit (popular fighting game subreddits such as r/fighters and r/ssbm), and Discord servers (online fighting game-based communities gamers use to talk about their games of choice and find others to play with).

A total of 427 participants began the study. 187 participants terminated participation part-way through the study, and thus were excluded. 14 participants were excluded for not meeting the listed inclusion criteria (e.g., age not within 18-65 years). An additional 49 participants were excluded for showing evidence of non-compliance on multiple tasks (e.g., lack of attention or effort resulting in errors rates greater than 20%), leaving a final participant pool of 177 fighting game players. Participants exhibiting non-compliance or otherwise problematic participation in only a single task were excluded from the analysis for said task but were still included in the remaining task analyses.

In order to place these participants into categories of gaming skill, demographic information was collected. Participants who reported themselves as “Amateur” or “Novice” skill levels were grouped into the Novice category for a total of 37 Novice players (32 male, 1 female, 4 non-binary; mean age = 22.5). Another 68 participants reported themselves as “Mid-level”; these players constituted the “Intermediate” skill category (62 male, 3 female, 3 non-binary; mean age = 23.1). To create our final skill category, “Top-level Expert,” players who self-identified as either “High-level” or “Top-level” were considered. To be categorized as an Expert, participants had to have been ranked on an official power rankings list for their competitive game (e.g., Panda Global Top 100 Rankings), have qualified to compete in a top-level eSports league (e.g., Summit Champions League), or have been identified by a reputable community figurehead as someone with comparable skill to be able to satisfy the prior criteria. 38 players who self-identified as “High-level” did not satisfy our criteria to be considered a true top-level expert, and thus were not included in our

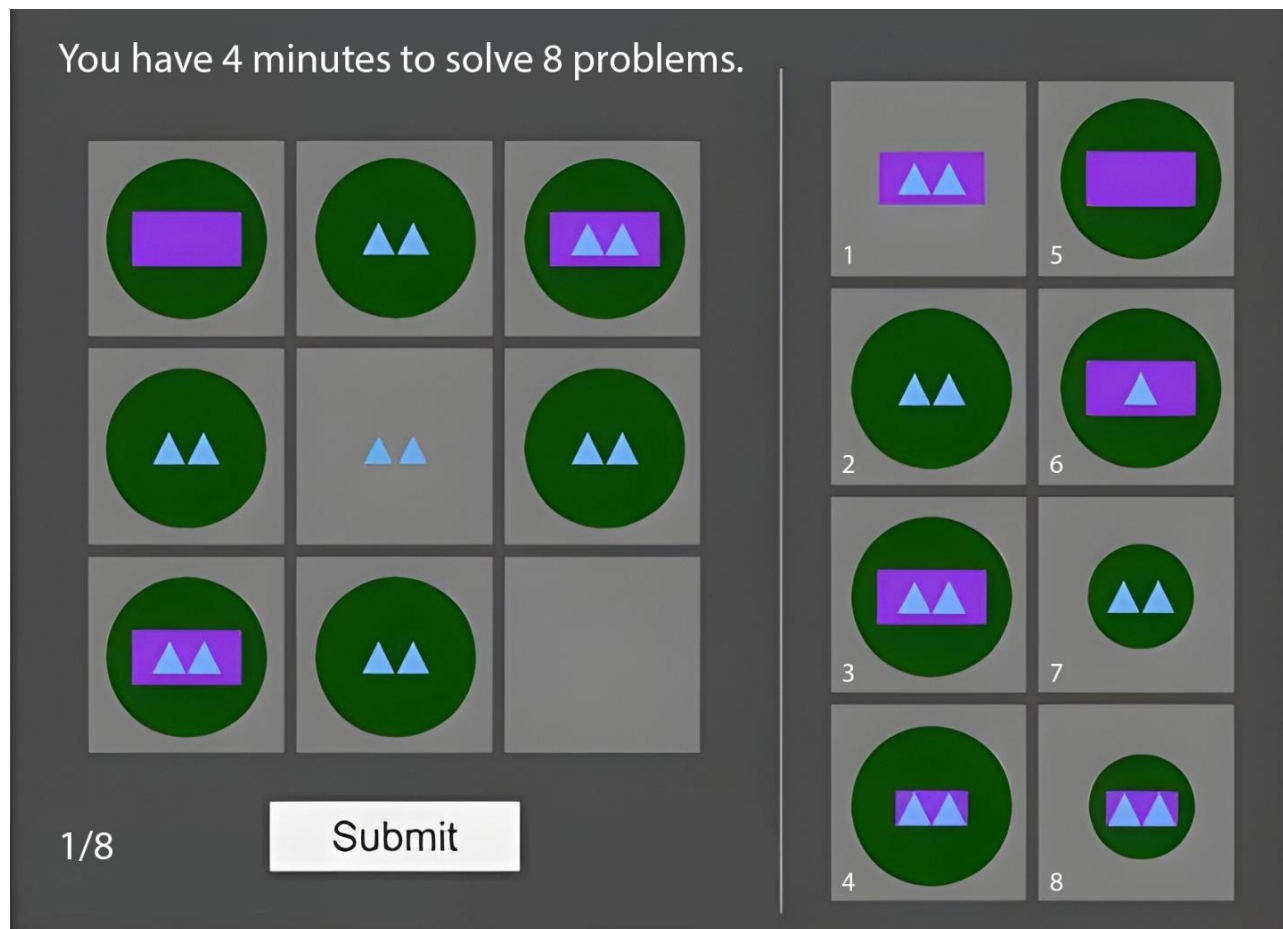
analysis (as it was unclear whether they belonged in the “intermediate” skill category). A remaining pool of 34 world-class fighting game experts was created (32 male, 1 female, 1 non-binary; mean age = 25) for a total of 139 final participants. Participants were entered into two (one per hundred participants) random drawings to win a \$100 Amazon gift card.

## Overview of Tasks and Questionnaires

Participants received a link which led to an online consent form. After providing consent, participants first completed a short questionnaire. This included questions meant to help assess the game players’ skill level (e.g., gaming username, games the individual played/competed in, highest achieved rank) as well as for demographically matching groups (e.g., age, sex/gender, education level). Participants then completed an online battery of seven cognitive tasks via the Qualtrics and Inquisit platforms. All participants completed the tasks in a fixed order: Matrix Reasoning, Serial Reaction Time, Corsi Block Tapping, Simple Visual Reaction Time, Simple Auditory Reaction Time, Paced Motor Timing, and Sustained Attention (see below for task details). All tasks aside from the first were downloaded and run locally on the participants’ computer, so as to prevent web-based inaccuracies for millisecond-level cognitive performance data. Participation in the full study took approximately 30 minutes.

## Cognitive Task Battery

**Matrix Reasoning Task:** The first assessment in the cognitive task battery was the University of California Matrix Reasoning Task (UCMRT), as a measure of fluid intelligence (Pahor et al., 2019). This task was run using Qualtrics software. On each trial of the task, participants viewed a 3x3 grid of items with one item missing. The participants’ goal was to indicate which of 8 possible items would logically complete the grid. Participants had 4 minutes to complete 8 trials. The dependent variable was the number of correct answers (see Figure 1 for example trial).



**Figure 1.** A sample trial from the matrix reasoning task, in which participants are instructed to choose the answer that logically completes the given grid (correct answer: choice 3).

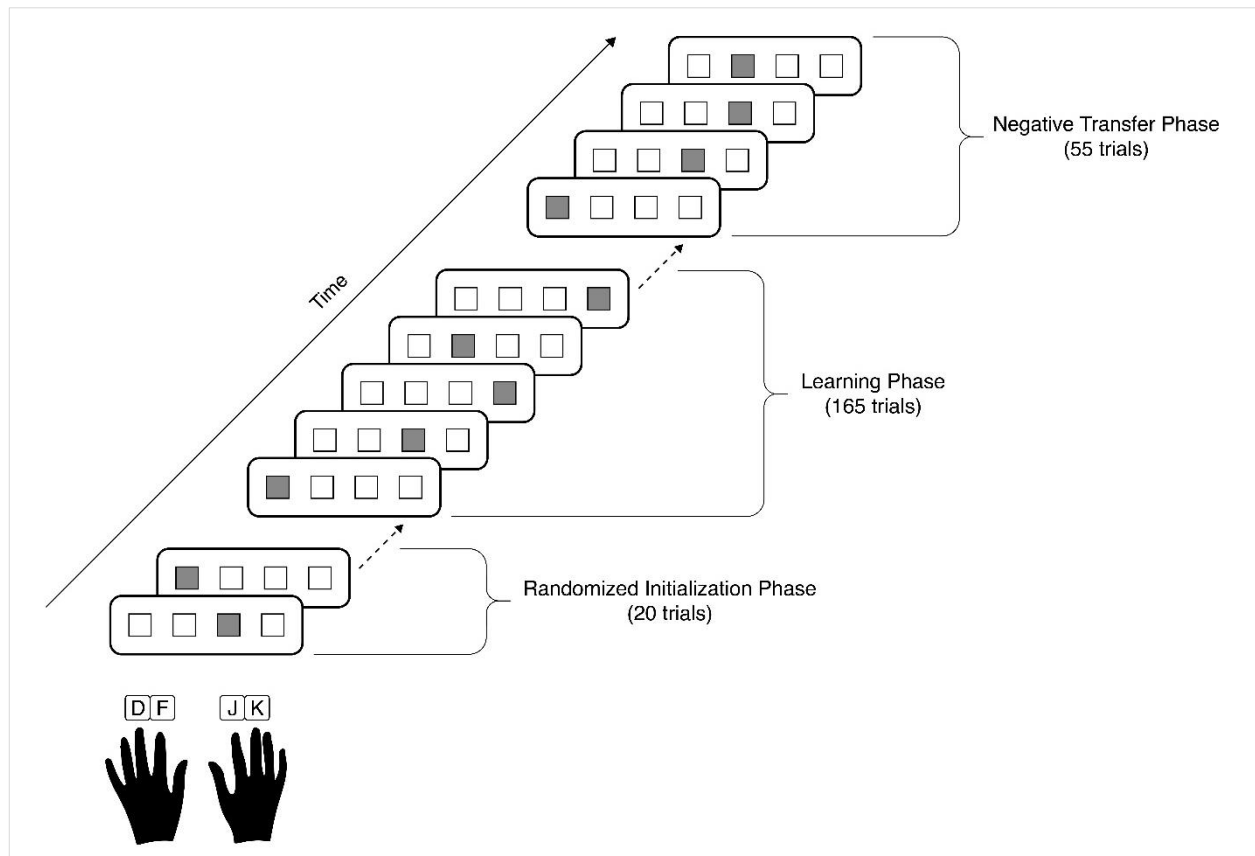
**Serial Reaction Time Task:** The second task was a modified version of a serial reaction time task (Nissen & Bullemer, 1987; Song et al., 2008). This and all subsequent tasks were run using Inquisit software. 4 gray boxes remained onscreen for the duration of this task, each corresponding to a keyboard key (see Figure 2). For each trial, participants pressed one of the four keys in response to the target stimulus, a red box, appearing over one of the corresponding 4 gray boxes. The task had three distinct phases that differed in terms of how the sequences of boxes were generated (although the transition from phase to phase was not made explicit to participants). The task began with 20 randomly generated trials (i.e., the red box could appear anywhere, independent of where it had been in the past). After this came the learning phase. Here the boxes that turned red at each moment in time were determined by an 11-node sequence. This sequence was repeated 15 times,

for a total of 165 learning trials. The final phase was the negative transfer phase. Here the sequence would occasionally be disrupted, as several nodes within the sequence changed pseudorandomly, breaking the established patterns for the final 55 trials. This phase is designed to be complementary to implicit sequence learning, as any gains made from the learning phase should be proportional to a decrease in performance in the final phase due to the impairing effect of negative transfer (i.e., we hypothesize that the group with the best performance on the learning block will have the worst performance on the negative transfer block).

Implicit sequence learning was measured via the difference in median response times over the first sequence iteration as compared to that of the final sequence iteration. Negative transfer was measured via the difference in median response times for the first 33 negative transfer trials

compared to the final iteration of the learned sequence. We chose to group these 33 trials for analysis to capture the strongest disruptive effect of

the negative transfer not only on incongruent trials, but also lingering effects on segments of the pattern that were not changed.



**Figure 2.** Visual representation of the serial reaction time task. Participants use the D, F, J, and K, keys on a keyboard to respond to a visual stimulus appearing at one of 4 respective locations. The task contains three phases which flow seamlessly together, unbeknownst to the participant. The first phase contains 20 trials which are randomly generated. The next 165 trials contain a hidden 11-node repeating sequence, which participants may learn implicitly. The final 55 trials contain a modified version of the repeating sequence in which some of the patterns have been altered. A participant who exhibits stronger learning of the implicit sequence should perform worse in this negative transfer phase, as their prior learning causes them to make errors when the learned patterns are broken.

**Corsi Block Tapping:** The third task of the battery was Corsi Block Tapping, as a measure of working memory (Berch et al., 1998; Corsi, 1972). Participants viewed a field of 9 squares, some number of which would light up, one after another, in a particular sequence. Following the conclusion of the sequence, participants were then asked to click on the squares in the same order to indicate their recollection of the sequence. The experiment started with a sequence length of three squares. Participants completed two trials of this length and if they got at least one of the two trials correct (i.e., all squares in the correct temporal order) the sequence length

was increased by one. This process continued until the participant either failed both trials, or they reached a maximum sequence length of 10. The dependent variable was the longest sequence length that the participant was able to correctly recall, also referred to as “blockspan.”

**Simple Reaction Time Tasks:** The fourth and fifth tasks of the battery measured simple reaction time (Bliss, 1892; Fry, 1975). Participants were asked to press the spacebar as fast as possible in response to a target stimulus. Both visual and auditory versions were utilized. In the visual version, the target stimulus was a



red circle. In the auditory version, the auditory stimulus was a 440 Hz audio beep. Participants completed 30 trials per task. The dependent variable was measured as median response times for each independent task after removing trials with early responses or responses over 1000 milliseconds.

**Paced Motor Timing Task:** The sixth cognitive task assessed rhythmic motor timing (Wittmann et al., 2007). Participants were asked to press the spacebar in synchronization with audio beeps occurring at regular intervals. The task had a paced condition, where the beeps remained throughout all trials, as well as an unpaced condition, where the beeps would cease halfway through the set of trials. In both conditions, participants were asked to maintain the rhythm established by the initial beeps. In addition, there were 3 discrete time intervals between the beeps, namely 1000, 2000, and 3500 milliseconds. Every participant completed all 6 conditions, each of which consisted of 20 intervals, in separate blocks. Participants completed all paced blocks before completing the unpaced blocks. Within the paced and unpaced blocks, the order of time intervals was randomized. The dependent variable was average temporal deviation (in milliseconds) from the correct rhythm.

**Sustained Attention Task:** The final element of the battery was a sustained attention task (Allan Cheyne et al., 2009; Robertson et al., 1997). Participants viewed a series of digits, each followed by a masking stimulus. Participants were instructed to press the spacebar as fast as they could in response to any digit except for the number 3, for which participants were not to respond. 18 practice trials were presented, followed by 225 test trials. The dependent variables for this task were median reaction time for go trials, as well as accuracy for no-go trials.

## Results (Experiment 1)

For two key reasons, we chose to analyze each task separately, rather than utilizing a composite or multivariate model. First, because one explicit goal of the design of our cognitive task battery was to tap a variety of cognitive constructs, there was no a priori reason to

expect performance on all tasks to be correlated, and a supplementary correlation matrix validates this assumption (see Figure 3). Second, and more importantly, in many cases the predictions for performance differences in the tasks differed from one another (e.g., we a priori expected reaction time results to be more strongly correlated with video game skill level than would be fluid intelligence).

For all tasks, the same general analysis strategy was employed (in the manner described in our pre-registered analysis plan). First, an ANOVA was run with video game skill level (i.e., Novice, Intermediate, Expert) as a between-participants factor to examine whether the three groups differed in performance. Then, if the main effect of video game skill level was significant, this was followed up by pairwise Tukey HSD post-hoc tests comparing the groups with one another.

**Matrix Reasoning Task:** An ANOVA was run on number of correct responses with video game skill level as the sole between-participants factor. The main effect of video game skill on matrix reasoning correct responses (out of 8 possible points) did not reach our significance threshold ( $F(2,136) = 1.09, p = .339, \eta^2 = .016$ ).

**Serial Reaction Task:** We excluded 2 participants (both Novices) who had an overall accuracy of less than 50%, resulting in 137 included participants.

An initial ANOVA was run on raw median response times for the first learning block sequence to determine if there were between-groups differences in baseline performance. The main effect of video game skill on reaction times (in ms) did not reach our significance threshold ( $F(2,134) = .05, p = .954, \eta^2 = .001$ ) when comparing the Novice, Intermediate, and Expert level gamers.

To ensure that any differences in baseline reaction times did not affect further dependent variables, response times were converted to be proportionate to baseline performance for all further analyses (i.e., learning magnitude was computed as  $(\text{initialRT} - \text{finalRT}) / \text{initialRT}$ , and negative transfer magnitude was computed as  $(\text{finalRT} - \text{NegativeTransferRT}) / \text{finalRT}$ ).

Separate ANOVAs were then conducted on the two proportional measures (magnitude of learning; negative transfer) with video game skill level as the sole between-participant factor. These effects did not reach our significance threshold (learning:  $F(2,134) = .55, p = .577, \eta^2 = .008$ ; negative transfer:  $F(2,134) = .72, p = .487, \eta^2 = .011$ ).

**Corsi Block Tapping Task:** An ANOVA was run on the longest recalled sequence length with video game skill level as the sole between-participant factor. The effect did not reach our significance threshold ( $F(2,136) = .02, p = .983, \eta^2 < .001$ ).

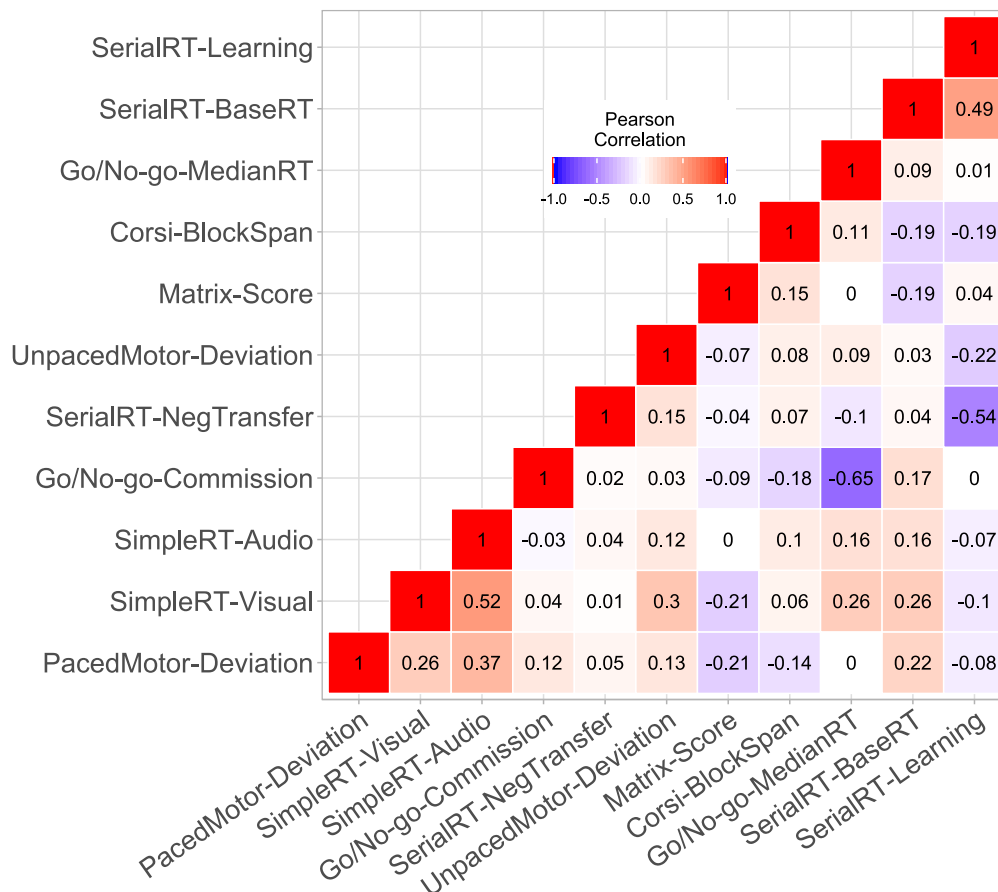
**Simple Reaction Time Tasks:** The two simple reaction time tasks (visual and auditory) were combined for the sake of analysis, and a two-way, repeated measures ANOVA was run on median reaction times from both tasks with task modality as the sole within-subjects factor and video game skill as the sole between-participants factor. The effect of task modality was not significant ( $F(1,136) = .01, p = .922, \eta_p^2 < .001$ ). A significant effect of group was observed ( $F(2,136) = 4.54, p = .012, \eta_p^2 = .063$ ), with Expert players being numerically faster than Intermediates, followed by Novices (see Table 1 for group statistics). Three Tukey HSD post-hoc tests were conducted comparing each group against the others. Significant between-groups differences were seen comparing Fighting Game Experts and Intermediates ( $p = .021, d = .57$ ), as well as between Experts and Novices ( $p = .023, d = .59$ ) but the difference between Novices and Intermediates ( $p = .947, d = .06$ ) did not reach significance. The interaction between modality and video game skill level was not significant ( $F(2,136) = .237, p = .789, \eta_p^2 = .003$ ).

**Paced Motor Timing Task:** We excluded 3 participants (1 Novice, 2 Experts) who pressed the spacebar 4 or more extra times per trial block. Remaining trials or trial blocks that were clear outliers (e.g., deviation scores above 1000ms, trial blocks with 10 or greater extra

taps or fewer than the 20 intended taps) were individually excluded. Our final sample included 136 participants.

An ANOVA was run with Feedback (paced/unpaced) and Interval (1000ms/2000ms/3500ms) as within-participants factors and video game skill level as the sole between-participants factor. The expected main effects of Feedback ( $F(1,133) = 4.84, p = .030, \eta_p^2 = .035$ ) and Interval ( $F(2,266) = 78.68, p < .001, \eta_p^2 = .372$ ) were found, suggesting that the lack of feedback within the unpaced conditions as well as longer time interval between beeps both significantly impaired performance. A significant interaction was also observed between Feedback and Interval ( $F(2,266) = 7.47, p < .001, \eta_p^2 = .053$ ), suggesting that a lack of feedback is particularly detrimental for longer time intervals. The core question for us was the main effect of gaming skill level, which did not reach our significance threshold ( $F(2,133) = 1.92, p = .151, \eta_p^2 = .028$ ). No interactions with group were significant.

**Sustained Attention Task:** Two ANOVAs were run to detect video game skill level differences in (1) median response times for go-trials and (2) accuracy on no-go-trials, as measured by percent commissions (failed response inhibition). A significant group difference was observed for median go-trial reaction times ( $F(2,136) = 5.50, p = .005, \eta^2 = .075$ ), with Fighting Game Experts performing faster than Intermediates, who performed faster than Novices. Tukey HSD post-hoc tests revealed significant differences between Novices and Experts ( $p = .012, d = .83$ ) as well as between Intermediates and Experts ( $p = .009, d = .66$ ), but not between Novices and Intermediates ( $p = .955, d = .056$ ). The effect of video game skill level on commission error percentage did not reach our significance threshold ( $F(2,136) = .19, p = .824, \eta^2 = .003$ ).



**Figure 3.** A correlation matrix containing all 15 dependent variables across all 7 cognitive tasks.

**Table 1.** Means and standard errors of cognitive task data for Novice, Intermediate, and Expert eSports players.

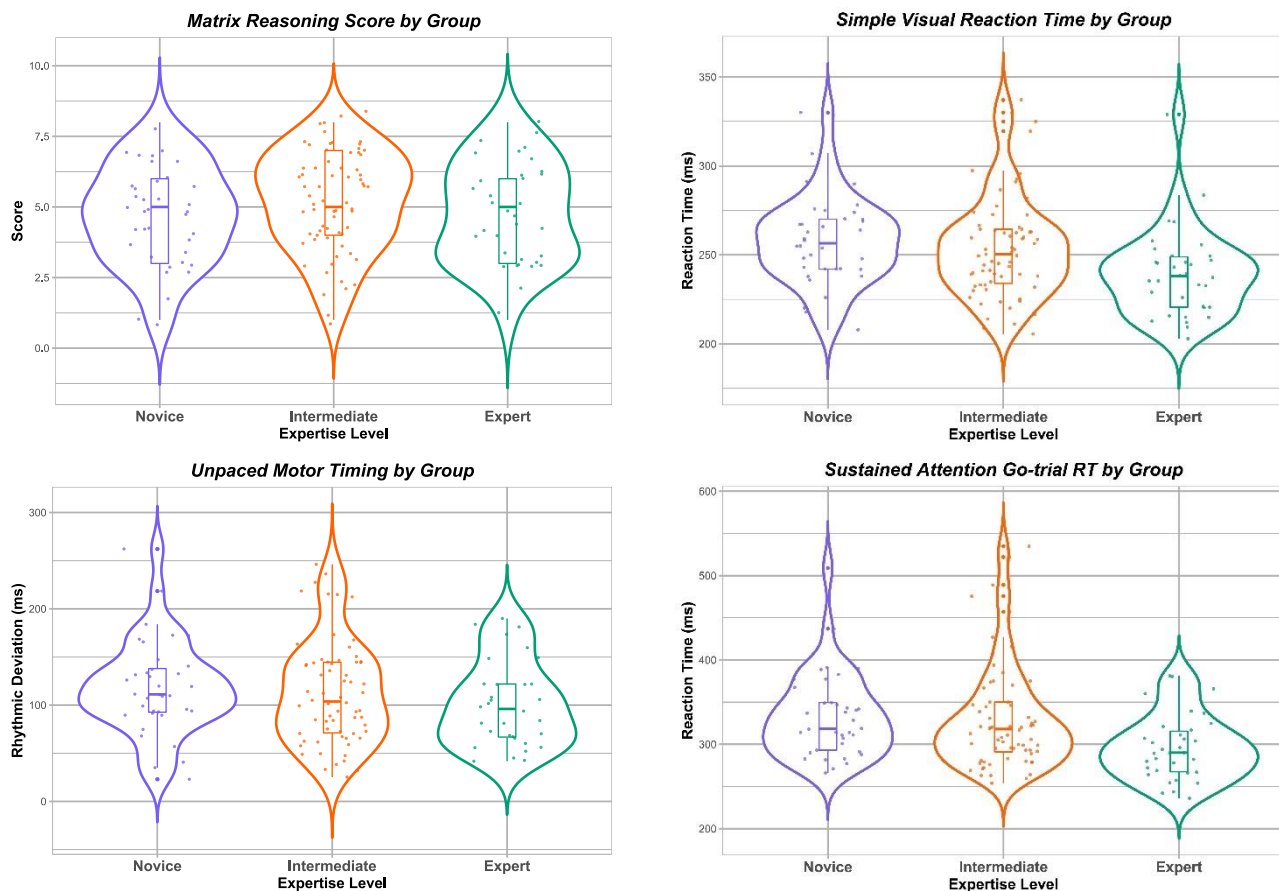
Measure	Novice <i>M (SE)</i>	Intermediate <i>M (SE)</i>	Expert <i>M (SE)</i>
Matrix reasoning			
Correct responses (8 total)	4.70 (.29)	5.18 (.22)	4.76 (.31)
Serial reaction time			
Base response time (ms)	383.81 (11.80)	388.26 (11.14)	383.49 (16.37)
Learning Prop (%)	.13 (.014)	.11 (.016)	.13 (.021)
Negative Transfer (%)	-.11 (.015)	-.10 (.013)	-.08 (.017)
Corsi block tapping			
Blockspan	7.05 (.16)	7.04 (.14)	7.09 (.23)
Simple reaction time			
Visual RT (ms)	260.97 (4.85)*	255.37 (3.58)#	239.43 (5.06)*.#
Auditory RT (ms)	257.74 (8.71)*	259.10 (6.43)#	237.50 (9.09)*.#
Total RT (ms)	259.35 (5.43)*	257.23 (4)#	238.46 (5.66)*.#
Paced Motor Timing			
Paced rhythm deviation (ms)	114.87 (7.82)	102.17 (5.69)	98.08 (8.29)
Unpaced rhythm deviation (ms)	147.75 (20.05)	139.84 (14.59)	102.89 (21.26)
Total rhythm deviation (ms)	131.31 (11)	121.01 (8)	100.49 (11.67)
Sustained Attention			
Go-trial RT (ms)	333.16 (8.25)*	330 (7.48)#	296 (6.59)*.#
Commission Error (%)	48.86 (3.45)	49.35 (2.65)	46.59 (3.63)

**Note:** When significant ( $p < .05$ ) differences are observed for exactly 2 of the 3 group comparisons, a combination of \* and # are used to denote the significant group differences.

## Discussion (Experiment 1)

Our most prominent hypothesis for cognitive performance differences between Fighting Game players of different skill levels was that reaction time, as a measure of processing speed, would be faster in correlation with video game skill. This hypothesis was largely supported by the data, as Experts' reaction times were significantly faster than Novices and/or Intermediates in the simple reaction time tasks as well as the go-trials for the sustained attention task (see Figure 4). Curiously, the baseline reaction times for the serial reaction time task were roughly equal across all skill groups. This may be a result of the baseline measurement being taken from the beginning of the task; participants may have still been getting used to the choice reaction format, and their initial median response times may not yet have reflected any true underlying differences in

processing speed. Within the serial reaction time task, we also expected higher skill level participants to exhibit greater implicit sequence learning and experience a stronger negative transfer effect when the implicit sequence was broken; these results did not reach significance. Our second main hypothesis was to find a null result when comparing fluid intelligence measures across skill level. In line with this hypothesis, matrix reasoning results did not significantly differ by skill level, although we note that there are many potential reasons a null hypothesis may fail to be rejected, therefore we can not claim our a priori hypothesis to be decisively confirmed. We also expected to see significant differences in working memory and sustained attention by skill level, but this was not substantiated via corsi block tapping data analysis nor go/no-go commission error analysis, respectively.



**Figure 4.** Violin plots for four of the tasks (Matrix Reasoning, Simple Visual Reaction Time, Unpaced Motor Timing, and Sustained Attention Go-trial RT) are presented. The plots include scattered data points as well as a nested box and whisker plot for each of the 3 participant groups (Fighting Game Novices, Intermediates, and Experts).

## Experiment 2: Fighting Game Experts vs Rhythm Game Experts vs NVGPs

This experiment aimed to replicate the design of the first experiment, this time incorporating the concept of “genre-specificity” by studying top-level expert groups from two different competitive gaming genres: fighting games and rhythm games. These world-class gamers were also compared against a demographically matched sample of Non-video-game players (NVGPs) who had little to no gaming experience. All participants underwent the same cognitive task battery as was used in Experiment 1. As with the first experiment, we expected a general effect of expertise to manifest as an increase in performance on all metrics, aside from fluid intelligence, for our expert groups when compared to the non-expert, NVGP group. All other hypotheses focused on the potential differences between expert groups, which may possibly be attributable to the inherent differences in mechanical and cognitive demands of each respective gaming genre. Presuming that reaction time would be more prudent to a dynamically changing, stochastic fighting game than to a deterministic, rehearsed rhythm game, we anticipated that fighting game experts will exhibit faster reaction times than rhythm game players. Similarly, we expected sustained attention performance to be better in the fighting game expert group. Conversely, we hypothesized that rhythm game players would outperform fighting game players on our paced motor timing task, since precise rhythm execution and maintenance seems to be a more archetypical demand of a rhythm game compared to a fighting game. We had no strong a priori expectations for the remaining tasks regarding any domain-specific expertise differences between our expert groups, and thus the analysis comparing performance on these tasks should be considered exploratory.

### Methods

All procedures were approved by the research ethics board at the University of Wisconsin-Madison. Study materials and preregistration can be found at <https://osf.io/zksqx/>.

### Participants

In addition to the 34 top-level fighting game players identified and presented in Experiment 1, Experiment 2 aimed to recruit a comparison group of expert competitors from another gaming genre – music/rhythm games – as well as a group of individuals with little to no gaming experience. Potential top-level rhythm game players were contacted for possible participation by the first author via email, direct messaging, and recruitment posts made to Twitter, and Discord servers (e.g., popular *Guitar Hero* and *osu!* communities). Individuals that were unlikely to be expert gamers of any type were recruited from the undergraduate student pool at a large midwestern university as well as from local area Facebook groups (i.e., that would consist of regular community members, such as local buy/sell/trade or community advertising pages).

Including the high-level expert participants discussed in Experiment 1, data were collected from a total of 697 individuals. 315 participants terminated participation part way through the study, and thus were excluded. 17 participants were excluded for not meeting the listed inclusion criteria (e.g., age not within 18-65 years). An additional 57 participants were excluded for showing evidence of non-compliance (e.g., not paying attention to tasks, lack of genuine effort).

Given the desire to examine cognitive abilities associated with high-level expertise in fighting and rhythm games, individuals’ demographics were examined to determine if they met the criteria to be considered a Fighting Game Expert, a Rhythm Game Expert, or a non-expert/NVGP.

Data from the same 34 participants (32 male, 1 female, 1 non-binary; mean age = 25) identified in Experiment 1 as experts of the fighting game genre are included here in Experiment 2. Among the 131 remaining participants, 17 participants (17 male; mean age = 21.3) were identified as experts of the rhythm game genre. To be considered a Rhythm Game Expert, participants had to have been ranked in the top 1% for their competitive game, have qualified to compete in a top-level eSports

league (e.g., CSC Elite League), or have been identified by a reputable community figurehead as someone with comparable skill to be able to satisfy the prior criteria. Drawing from our total pool of non-experts, we constructed a comparison sample that was demographically matched as closely as possible to the expert groups. This sample consisted of all males from the undergraduate student pool/local community online groups that successfully completed the study as well as the 2 females from those pools that most closely matched the 2 non-male expert participants in terms of age and education level. Our final non-expert group consisted of 28 participants (26 male, 2 female; mean age = 20.46).

Non-student participants who were not already included in Experiment 1 were entered into two additional (one per hundred participants) random drawings to win a \$100 Amazon gift card. Student participants received course credit for their participation.

## Overview of Tasks

The consent form, demographics survey, and cognitive task battery were all identical to those used in Experiment 1. Please refer to the previous methods section for more information.

## Results (Experiment 2)

All procedures and analyses were identical to those explained in Experiment 1, with the exception of video game group membership (i.e., Fighting Game Expert, Rhythm Game Expert, Non-video game players) being the sole between-participants factor.

**Matrix Reasoning Task:** An ANOVA was run on number of correct responses with video game group membership as the sole between-participants factor. The main effect of video game group membership on matrix reasoning correct responses (out of 8 possible points) did not reach our significance threshold ( $F(2,76) = 1.54, p = .222, \eta^2 = .039$ ).

**Serial Reaction Task:** We excluded 2 participants (both NVGPs) who had an overall

accuracy of less than 50%, resulting in 77 included participants.

An initial ANOVA was run on raw median response times for the first learning block sequence to determine if there were between-groups differences in baseline performance. A significant effect of video game group membership was observed ( $F(2,74) = 17.31, p < .001, \eta^2 = .319$ ), with Rhythm Game Experts being numerically faster than Fighting Game Experts being faster than NVGPs (see Table 2 for group statistics). Follow-up Tukey HSD post-hoc tests revealed significant between-groups differences when comparing Fighting Game Experts to NVGPs ( $p = .001, d = .90$ ), Rhythm Game Experts to NVGPs ( $p < .001, d = 2.35$ ), as well as between Fighting and Rhythm Game Experts ( $p = .018, d = .90$ ).

To ensure that these differences in baseline reaction times did not affect further dependent variables, response times were converted to be proportionate to baseline performance for all further analyses, as was done in Experiment 1.

Separate ANOVAs were then conducted on the two proportional measures (magnitude of learning; negative transfer) with video game group membership as the sole between-participant factor. While the groups differed in terms of numerical performance in the direction pre-specified in our analysis plan (i.e., greater magnitude of learning and greater negative transfer in the expert groups), these between-group differences did not reach our significance threshold (learning:  $F(2,74) = .91, p = .407, \eta^2 = .024$ ; negative transfer:  $F(2,74) = 2.59, p = .082, \eta^2 = .065$ ).

**Corsi Block Tapping Task:** An ANOVA was run on the longest recalled sequence length with video game group membership as the sole between-participant factor. The effect did not reach our significance threshold ( $F(2,76) = .59, p = .556, \eta^2 = .015$ ).

**Simple Reaction Time Tasks:** We excluded 1 participant (an NVGP) from each task for whom at least 20% of trials were considered “bad trials” (e.g., early responses, responses over 1000ms, or omissions). The resulting sample included 78 participants for each task.

The two simple reaction time tasks (visual and auditory) were combined for the sake of analysis, and a two-way, repeated measures ANOVA was run on median reaction times from both tasks with task modality as the sole within-subjects factor and video game group membership as the sole between-participants factor. No significant effect of task modality was observed ( $F(1,75) = .84, p = .363, \eta_p^2 = .011$ ). A significant effect of group was observed ( $F(2,75) = 34.83, p < .001, \eta_p^2 = .482$ ), with Rhythm Game Experts performing faster than Fighting Game Experts, who performed

faster than NVGPs. Three Tukey HSD post-hoc tests were conducted comparing each group against the others. Significant between-groups differences were seen comparing Fighting Game Experts to NVGPs ( $p < .001, d = 1.97$ ) as well as Rhythm Game Experts to NVGPs ( $p < .001, d = 2.03$ ), but the difference between Fighting and Rhythm Game Experts was not significant ( $p = .978, d = .06$ ). The interaction between modality and video game group membership was not significant ( $F(2,75) = .16, p = .854, \eta_p^2 = .004$ ).

**Table 2.** Means and standard errors of cognitive task data for top-level experts of the Fighting and Rhythm game eSports genres, as well as a non-expert control of non-video game players.

Measure	Fighting Game Experts <i>M (SE)</i>	Rhythm Game Experts <i>M (SE)</i>	NVGPs <i>M (SE)</i>
Matrix reasoning			
Correct responses (8 total)	4.76 (.31)	4.82 (.41)	4.04 (.36)
Serial reaction time			
Base response time (ms)	383.49 (16.37)*	317.18 (10.13)*	461 (14.84)*
Learning Proportion	.13 (.021)	.09 (.030)	.09 (.032)
Negative Transfer Proportion	-.08 (.017)	-.15 (.030)	-.08 (.023)
Corsi block tapping			
Blockspan	7.09 (.23)	7.35 (.32)	6.93 (.22)
Simple reaction time			
Visual RT (ms)	239.43 (5.06)*	242.44 (7.96)#	300.39 (6.39)*.#
Auditory RT (ms)	237.50 (9.09)*	230.89 (11.91)#	295.17 (9.45)*.#
Total RT (ms)	238.46 (5.66)*	236.66 (7.32)#	297.78 (5.81)*.#
Paced Motor Timing			
Paced rhythm deviation (ms)	98.08 (8.29)*	84.71 (12.68)#	147 (10.36)*.#
Unpaced rhythm deviation (ms)	102.90 (21.26)*	97.69 (21.47)#	145.46 (18.12)*.#
Total rhythm deviation (ms)	100.49 (11.67)*	92.90 (13.34)#	146.23 (10.89)*.#
Sustained Attention			
Go-trial RT (ms)	296 (6.59)	297.30 (13.73)	321.48 (13.1)
Commission Error (%)	46.59 (3.63)*	54.13 (6.11)	64.46 (4.64)*

**Note.** When significant ( $p < .05$ ) differences are observed for exactly 2 of the 3 group comparisons, a combination of \* and # are used to denote the significant group differences.

**Paced Motor Timing Task:** We excluded 3 participants (2 Fighting Game Experts, 1 NVGP) who pressed the spacebar 4 or more extra times per trial block. Remaining trials or trial blocks that were clear outliers (e.g., deviation scores above 1000ms, trial blocks with 10 or greater extra taps or fewer than the 20 intended taps) were individually excluded. Our final sample included 76 participants.

An ANOVA was run with Feedback (paced/unpaced) and Interval (1000ms/2000ms/3500ms) as within-participants factors and video game group membership as the sole between-participants factor. The expected main effect of Interval was found ( $F(2,146) = 59.38, p < .001, \eta_p^2 = .463$ ) suggesting that shorter rhythmic intervals are easier to keep pace with, although no main effect of Feedback was observed ( $F(1,73) = .30,$

$p = .586$ ,  $\eta_p^2 = .004$ ), suggesting that the lack of feedback within the unpaced conditions did not significantly impair performance when collapsed across all time intervals. There was a significant interaction between Feedback and Interval ( $F(2,146) = 3.15$ ,  $p = .046$ ,  $\eta_p^2 = .044$ ), suggesting that a lack of feedback is more detrimental for longer time intervals. The core question for us was the main effect of group, which was found to be significant ( $F(2,73) = 6.60$ ,  $p = .002$ ,  $\eta_p^2 = .162$ ), with Rhythm Game Experts having the numerically smallest timing deviations from the correct motor rhythm, followed by Fighting Game Experts, followed by NVGPs. Tukey HSD post-hoc tests were conducted, revealing significant between-group differences among Fighting Game Experts and NVGPs ( $p = .006$ ,  $d = .86$ ) as well as Rhythm Game Experts and NVGPs ( $p = .008$ ,  $d = .98$ ), but no significant difference between Fighting and Rhythm Game Experts ( $p = .888$ ,  $d = .14$ ). No interactions with group were significant.

**Sustained Attention Task:** We excluded 4 participants (2 Rhythm Game Experts, 2 NVGPs) for whom over 20% of trials were erroneous omissions of response, resulting in 75 included participants.

Two ANOVAs were run to detect video game group membership differences in (1) median response times for go-trials and (2) accuracy on no-go-trials, as measured by percent commissions (failed response inhibition). The effect of video game group membership on median go-trial reaction times did not reach our significance threshold ( $F(2,72) = 1.93$ ,  $p = .153$ ,  $\eta^2 = .051$ ), however a significant group difference was observed for percent commissions ( $F(2,72) = 4.63$ ,  $p = .013$ ,  $\eta^2 = .114$ ), with Fighting Game Experts exhibiting the least commission error, followed by Rhythm Game Experts, followed by NVGPs. Follow-up Tukey HSD post-hoc tests revealed significant between-groups differences when comparing Fighting Game Experts to NVGPs ( $p = .009$ ,  $d = .80$ ), but not between Rhythm Game Experts and NVGPs ( $p = .340$ ,  $d = .44$ ), or Fighting and Rhythm Game Experts ( $p = .530$ ,  $d = .34$ ).

## Discussion (Experiment 2)

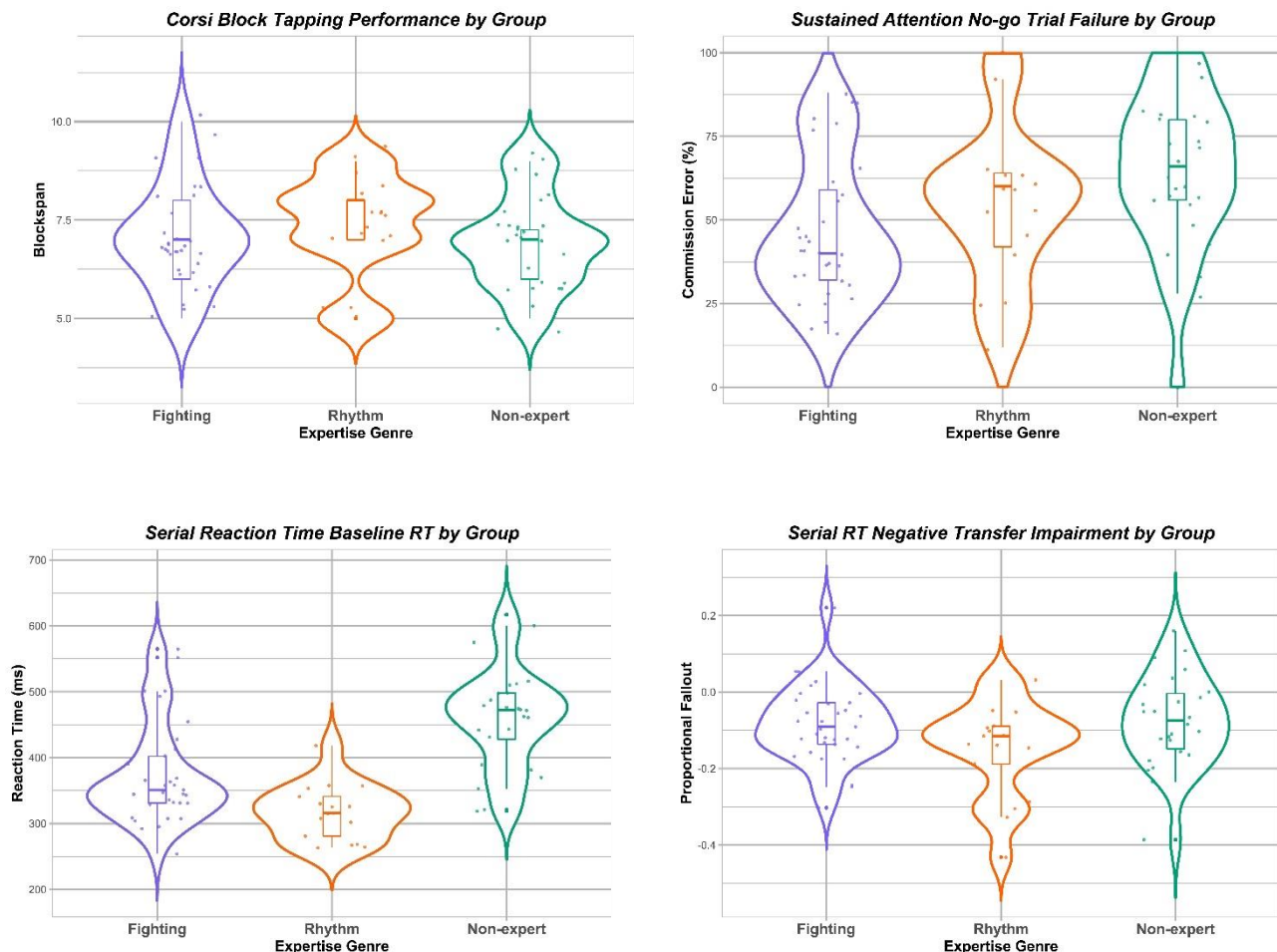
We expected top-level video game expertise to place different cognitive loads upon the player, by virtue of differences inherent to each genre and their core mechanics that must be perfected to achieve the highest levels of performance. Therefore, our main a priori hypotheses revolved around these proposed differences. One such hypothesis was that Rhythm Game Experts would perform better at the paced motor timing task when compared to Fighting Game Experts, since the skill of rhythm maintenance would seem to be more heavily taxed in a rhythm game. Our task results are numerically in line with this prediction. However, the difference was not large enough to reach significance and thus we cannot indicate that this hypothesis was supported. One peculiar finding regarding the paced motor timing task is the lack of a significant main effect of feedback in Experiment 2, in contrast to the observed effect from Experiment 1. Looking into our data from Experiment 2, we see that there were a small number of participants in the NVGP group who performed poorly enough in the unpaced condition that they were deemed outliers and excluded from further analysis, in line with our predetermined exclusion criteria. We had assumed that a 1000ms leniency would be an appropriate cutoff for determining genuine, effortful participation in the task, but in retrospect it seems that some participants were quite close to this range while still exhibiting otherwise genuine effort on the task. We re-ran the analysis after re-introducing the appropriate near-outliers, and although we still do not observe a significant p-value ( $p = .131$ ), we do see an effect size nearly identical to that of Experiment 1 ( $\eta_p^2 = .031$ ).

Another hypothesis was expecting fighting game players to exhibit better sustained attention, as the dynamic nature of a competitive fighting game may require more patience and vigilance than a deterministic rhythm game. Similar to the first hypothesis, the Fighting Game Experts did exhibit the least commission error, or no-go failure, of all groups (see Figure 5). However, again, the difference between Fighting and Rhythm Game Experts did not reach significance. This same trend was true for the measures of learning and negative transfer within the implicit sequence learning



aspect of the serial reaction time task. One result we did not have an a priori prediction for was baseline reaction times within the serial reaction time task. The data showed that rhythm game players exhibited significantly better baseline performance for the choice reaction task. This may be due to the task itself somewhat resembling popular keyboard-based rhythm games such as *Flash Flash Revolution*, where the player has four fingers spread across the keyboard and presses a key as a directional arrow passes over a target location. To the layman, reaction time may not be considered a key aspect of rhythm games, but at the highest levels of performance, experts are forced to play at lightning-fast speeds, sometimes reaching

over 30 notes per second. With this in mind, it becomes easier to see how reaction times in these choice selection scenarios may be a skill that is loaded upon very highly at top levels, and may explain why this particular test, and no other measures of reaction time, showed such a large difference between expert groups. The fact that no such baseline RT differences were observed in Experiment 1 across all fighting game skill levels for this particular task supports the hypothesis that this result is more strongly related to domain specific skills, rather than an overall effect of expertise.



**Figure 5:** Violin plots for four of the tasks (Corsi Block Tapping, Sustained Attention no-go Failure, Serial Reaction Baseline RT, and Serial Reaction Negative Transfer Fallout) are presented. The plots include scattered data points as well as a nested box and whisker plot for each of the 3 participant groups (Fighting Game Experts, Rhythm Game Experts, Non-expert NVGPs).

As with Experiment 1, we expected a general effect of expertise, where experts of both domains would tend to perform better than non-experts, i.e., non-video-game players. This effect was found for serial reaction time, simple reaction time, and paced motor timing. In line with the first experiment, we did not expect to see, and did not see, significant differences in fluid intelligence. Also, we expected to see differences in working memory between groups, but the Corsi block tapping results showed no group differences.

## General Discussion

Based on prior work examining the relationship between video game play and cognitive performance, we expected to see higher skilled game players exhibit greater levels of performance on some, but not all, cognitive tasks being measured (Bediou et al., 2018, 2023; Dale et al., 2020; Dale & Green, 2017; Green & Bavelier, 2003; Large et al., 2019; Li et al., 2020). Furthermore, this study aimed to delve deeper into the effect of genre specificity, whereby the unique characteristics and mechanics of the fighting game and rhythm game genres may load upon cognitive faculties in different ways at the highest levels of skill, and that this may manifest in enhanced performance in each group for those cognitive tasks that employ the same faculties that are heavily loaded upon by their respective games. Some of these hypotheses were supported by our data analysis as described above, particularly for the general effect of expertise, although many of these anticipated effects, despite generally occurring in the predicted direction, did not reach statistical significance. A salient example of this is found within the paced motor timing task. Across both studies, the five groups that took this test were Non-video-game players, Fighting Game Novices, Intermediates, Experts, and Rhythm Game experts. Our a priori hypothesis supposed that rhythmic motor performance would increase in line with the order of the groups, as the general effect of expertise would be the driving factor for the first four groups and the genre specific expertise of the rhythm game top players would help them especially excel at this particular task.

Numerically, the data followed this pattern exactly, with the mean motor timing deviation being 146.23ms, 131.31ms, 121.01ms, 100.49ms, and 92.90ms, respectively. The fact that the core comparisons failed to reach the level of statistical significance may reflect the fact that our sample sizes are inherently limited. An unfortunate tradeoff when comparing world-level experts of relatively niche domains is that there are very few top-level experts to begin with (necessarily meaning either having somewhat small *N*s or else loosening the criteria for “expert level” performance, which arguably no longer addresses the question of interest). In this sense, our sampling strategy was not driven by an expected power analysis, but simply by availability of experts. As such, our final sample was not powered to detect effects smaller than those in the medium-to-large range (e.g., the non-significant difference between expert groups in the Sustained Attention task was associated with a Cohen’s *d* of 0.34 - which is in the small-to-medium range).

The notion of effect size brings up an even more pressing matter, however. Even if every group difference we hypothesized were to have reached the level of statistical significance, the effect sizes are not large enough to, on their own, explain a majority of variance regarding actual video game performance. If the single most important factor in whether an individual could become one of the greatest eSports competitors in the world was indeed a matter of cognitive faculties such as reaction time, working memory, or sequence learning, then we could reasonably expect that the difference in cognitive task performance would be quite profound when comparing said world-class players to individuals with little to no video game playing experience, but this is simply not what was found.

One possibility regarding the lack of differences between the expert groups is that the cognitive tasks do in fact load more heavily upon both game types (rather than one game type disproportionately). For instance, it is possible that the need to execute button sequences in a fighting game (e.g., for “combos”) could load upon rhythmic motor

control constructs to a similar degree as in a rhythm game. A second possibility pertains to the match of expertise in our expert groups. Although in both cases we sought to recruit “true experts,” it is difficult to specify the degree to which experts in two very different domains are “similarly expert.” While our classification criteria were meant to provide as clear a match as possible, there remains the potential that one group was in fact more expert than the other. Finally, it could be the case that those who reach the highest echelons of fighting and rhythm games have a more “rounded out” cognitive profile. The classic question of whether these cognitive skills are being trained over time in these games or that a naturally high level of ability in key cognitive constructs leads particular individuals to rise to the top of competition remains unanswered. Some work, such as a recent, comprehensive meta-analysis by Bediou and colleagues (2023) offers support for causal inferences to be drawn with regard to video game training augmenting cognition, although future work may look to employ longitudinal designs to document how an individual’s level of cognitive performance may change along the full time-course of acquiring expertise in a particular domain.

These hypotheses do little, however, to account for the lack of several differences between the expert and non-video-game player groups. Alternatively, maybe these cognitive faculties are simply less impactful in skilled video game performance than may have been previously thought, or perhaps these relatively contrived cognitive tasks are too far removed from the actual game environments in which these players perform to measure these constructs effectively. Clearly then, more research is needed to elucidate the hidden factors underpinning these types of extreme expertise. Additional future work can tackle the causal question of whether competitive video game performance can be enhanced through the directly targeted training of the most relevant cognitive faculties, or rather if procedural components such as the optimization of practice methods and training tools may be much more effective in improving performance for the sake of eSports competition, as well as for a generally greater understanding of the building blocks of fine motor and cognitive skill acquisition.

## Supplemental Online Materials

Study materials and OSF preregistration available at: <https://osf.io/zksqx/>

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## Authors’ Declarations

The authors declare that there are no personal or financial conflicts of interest regarding the research in this article.

The authors declare that the research reported in this article was conducted in accordance with the Ethical Principles of the *Journal of Expertise*.

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