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Need for speed: Applying ex-Gaussian modeling techniques to examine intra-individual reaction time variability in expert Tetris players

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Abstract

Studies have shown that video game players exhibit superior performance to non-video game players on a number of cognitive tasks. Methods to compare the groups have mainly involved using measures of central tendency such as the mean without examining intra-individual differences in performance. In the present study, top-ranking Tetris players and novice Tetris players completed a reaction time cognitive task. Results show that the top-ranking players exhibit faster reaction times compared to novice players. Beyond the mean RT, we used the ex-Gaussian modeling technique and found differences in variability and attention between the two groups. Future studies can use modeling techniques such as the ex-Gaussian distribution to analyze the whole distribution at an individual level beyond measures of central tendency and further examine the behavioral differences between video game players and non-video game players.

Keywords: Tetris; extreme expertise; reaction time distribution; Ex-Gaussian distribution

Introduction

Previous research has shown that playing video games improves cognitive abilities. Some of these cognitive abilities include visual attention (Green & Bavelier, 2003; Dale, Kattner, Bavelier, & Green, 2019), probabilistic inference (Green, Pouget, & Bavelier, 2010), executive control (Li, Huang, Li, Wang, & Han, 2020), and reaction time (Pardina-Torner, Carbonell, & Castejón, 2019; Dye, Green, & Bavelier, 2009; Pluss et al., 2020). Other research has failed to find benefits of playing video games to improve spatial visualization skills (Sims & Mayer, 2002) and reaction time (van Ravenzwaaij, Boekel, Forstmann, Ratcliff, & Wagenmakers, 2014). In this paper, we argue that, among other things, the methods used to analyze data comparing video game players to non-video game players at the group level may contribute to some of these inconsistencies. We use a classic reaction time experiment to investigate if playing video games is associated with faster response times.

Reaction time experiments have been used to understand how reaction time (mental speed) differs for different populations such as younger vs older people (Deary, Liewald, & Nissan, 2011), professional video gamer players vs non-players (Pluss et al., 2020), and children with Attention-deficit/hyperactivity disorder (ADHD) vs those that do not have ADHD (Gmehlin et al., 2014), to name just a few. It is interesting to examine reaction time to try and understand the underlying cognitive processes responsible for these differences both at the group level and for the individuals within the group.

Reaction time (RT) distributions are usually positively skewed which means applying normal statistical methods might give incorrect results (Heathcote, Popiel, & Mewhort, 1991; Rousselet & Wilcox, 2018). It makes sense to remove RTs on the lower bound faster than 100ms attributed to fast guesses as that is the minimum threshold for stimulus perception and response (Whelan, 2008). On the upper bound, researchers deal with skewness in the data by removing RTs beyond a certain threshold such as 1500ms or above 3 standard deviations from the mean. However, there is no standard rule for dealing with slow RTs because it depends on the specific data and it can be challenging to separate outliers from real processes.

As other authors have noted, using measures of central tendency does not work for data that is not symmetrical (as most RT data is) (Balota & Yap, 2011), leads to misinterpretation of the data (Heathcote et al., 1991), and could mask interesting insights from behavior that results in fast and slow responses (Whelan, 2008). In other words, it might be insufficient to use mean RT alone to examine performance differences between groups of people.

An alternative that has been proposed is to analyze the whole distribution using modeling approaches to consider trial by trial changes in RT for the individual within a group (Balota & Yap, 2011; Heathcote et al., 1991). The ex-Gaussian function is a mathematical combination of the exponential and Gaussian (mean) distribution. It provides three estimates: mu, sigma, and tau. Mu and sigma represent the mode and standard deviation of the Gaussian component, respectively. Tau represents the mean and standard deviation of the exponential component (Balota & Yap, 2011). The ex-Gaussian provides a better fit for reaction time distributions compared to the gamma or lognormal distributions (Heathcote et al., 1991).

The ex-Gaussian approach has been used to examine intra-individual variability in inhibition for children with ADHD. The results showed a difference in Mean RT between the ADHD and control groups. However, the ex-Gaussian analysis found no difference for mu and a difference for sigma and tau suggesting that the ADHD group had higher variability than the control and many more slower reaction times compared to the control group (Gmehlin et al., 2014). These subtle behavioral differences would have been missed by only conducting an analysis of the Mean RT.

Using this approach, we can estimate ex-Gaussian parameters for RT data and examine individual differences between video game playing (VGP) and non-video game playing (nVGP) groups beyond what the mean can tell us. We show for the first time that by using ex-Gaussian modeling approaches, we can better tease apart the differences between video game playing individuals and non-video game playing individuals.

Assessing Expertise

There is a vast body of literature examining the effects of video games on cognitive abilities using a variety of methods to recruit and organize subjects (Green & Bavelier, 2003; Dale et al., 2019; Boot, Kramer, Simons, Fabiani, & Gratton, 2008; Li et al., 2020; Waris et al., 2019; Toth, Kowal, & Campbell, 2019; Gobet et al., 2014). There are two main methods used to classify and compare subjects in experimental and control groups: intervention and cross-sectional. With the intervention approach, subjects who initially have no gaming experience are trained using a video game of interest (experimental group) and compared to a control group (passive or active control group playing a different unrelated game). For both groups, measures of the cognitive abilities of interest are collected before and after the training intervention (Boot et al., 2008). With the cross-sectional approach, participants are categorized into video game playing (VGP) and non-video game playing (nVGP) groups based on self-reports of time spent playing video games. The groups are then compared on the cognitive abilities of interest to examine any differences that may exist as a result of playing video games (Dale et al., 2019; Waris et al., 2019).

Using an intervention approach would allow us to follow video game skill development and changes in cognitive abilities in a controlled setting. However, developing expertise may take months, years, or even decades to develop which may make such studies challenging to conduct in a laboratory setting. Recent research has begun to recruit subjects using ranking scores from E-sport tournaments such as League of Legends (Li et al., 2020) or Counter-Strike: Global Offensive (Toth et al., 2019). We followed this approach and recruited our VGP group from the top-ranking players at the annual Classic Tetris World Championship (CTWC) [1].

Tetris As A Research Paradigm

Tetris is a puzzle video game in which the player's objective is to maximize points by creating and clearing one or more horizontal lines. A zoid (Tetris piece) drops from the top of the board; it is rotated and translated so that it stacks with the other zoids on the board, ideally without leaving gaps. As the game progresses, the board configuration changes with each zoid placement. The game begins slowly (with the unhampered zoid requiring 16s to drop from top to bottom) but quickly becomes faster (e.g., at level 9 that same drop takes 2s, at level 18 1s, and at level 29 1/3s). An example of a Tetris board from the Meta-T version (Lindstedt & Gray, 2015) of the classic Tetris game is shown in Figure 1.

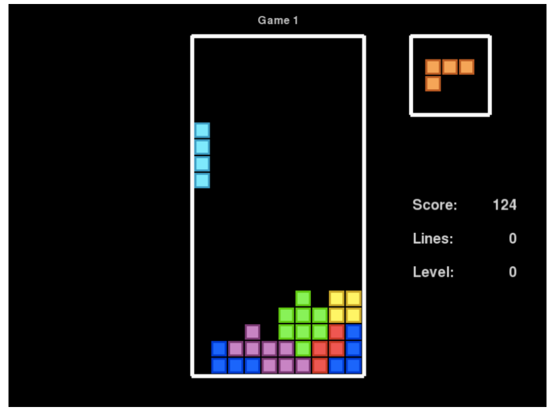

Figure 1: Screen-shot of a Tetris board during a game.

Tetris is one of the most popular video games in the world and draws many expert players to the annual Classic Tetris World Championship (CTWC, n.d.). This means we can collect a rich source of data from these extreme experts and compare their performance on a reaction time experiment with other less skilled players to explore differences in their mental speed.

Video games such as Tetris can be used as experimental paradigms to focus on processes such as perception, decision making, and skill acquisition (Gray, 2017). Tetris also provides a favorable environment for such a study because it is a dynamic task environment that can be used to carry out experiments as well as to observe and to analyze human behavior.

Aims of the current study

The purpose of this study is to identify whether top-ranking players in a prominent game (Tetris) exhibit faster reaction times at both the group and individual level using ex-Gaussian modeling techniques. Tetris has predominantly been classified as game that involves spatial skills (Pilegard & Mayer, 2018) and 'demands focus on one object at a time' (Green & Bavelier, 2003, p. 536). While this is true, we also posit that Tetris involves significant coordination of perception and action especially at the higher levels of the game where zoids have to be positioned on the board in 1/3s. We are also interested in applying the ex-Gaussian technique to examine individual differences in reaction time beyond using measures of central tendency. We hypothesize that the VGP group will exhibit faster reaction times than the nVGP group from previous research on video games (Morin-Moncet, Therrien-Blanchet, Ferland, Théoret, & West, 2016; Dye et al., 2009; Hubert-Wallander, Green, Sugarman, & Bavelier, 2011) and because of the dynamic nature of Tetris especially at the high levels where Tetris experts play.

[1] Link to a CTWC match: `https://youtu.be/5sxMqLjTv6k`

Methods

Participants

Video Game Playing Group (VGP) Twenty-two participants (21 male, 1 female) with a mean age of 20.8 years (SD = 7.1) were recruited from the top-ranking players attending the 2020 annual Classic Tetris World Championship (CTWC). Player rankings are usually determined based on the ELO rating for chess and multiplayer online battle arena games such as League of Legends (Li et al., 2020). However, Tetris doesn't officially use such a system. Players are ranked based on the highest score obtained during the qualifying rounds and tournament brackets of the CTWC. The VGP group was recruited through advertisements posted in online Tetris forums and via word of mouth.

Non-Video Game Playing Group (nVGP) Thirty-seven participants (17 male, 19 female, 1 did not say) with a mean age of 19.7 years (SD = 2.7) were recruited from introductory undergraduate psychology and cognitive science courses at a Rensselaer Polytechnic Institute. Participants in the nVGP group had previously completed a gaming history survey asking about the time spent playing Tetris. On average, they reported playing less than 1 hour per week. The nVGP group signed up for the study through the university research participant pool system.

To be eligible for the study, participants reported normal or corrected to normal vision and no history of seizures. The Institutional Review Board approved this study, and all participants provided written informed consent.

Procedure

The study at large consisted of 6 cognitive tasks administered remotely over an hour-long session. All tasks were developed and presented using E-prime software (Psychology Software Tools, Inc., 2016). Participants were sent information via email on how to remotely access the tasks with instructions to complete the study in a distraction free environment. In this article, we only present data from one of the tasks that the participants completed: a Reaction Time task (Deary et al., 2011).

Reaction Time Task Our version of the Reaction time task was an exact replication of the original task developed by Deary et al. (2011) in terms of task design and number of trials to reliably make between-group comparisons of reaction time. The Reaction Time (RT) task consisted of two blocks: Simple RT block and Choice RT block. During the Simple RT block, participants responded with the space bar each time the letter X appeared in a square on the screen for each trial. Participants completed 8 practice and 20 test trials. The inter-stimulus interval (time between response and the next trial) varied randomly between 1 and 3 seconds. The measures of interest during the Simple RT block was RT.

The Choice RT block consisted of four horizontally placed squares on the screen. Each square had a corresponding key assigned to it on the keyboard. On each trial, participants had to press one of the four keys on the keyboard depending on the position where the letter X appeared. Participants were instructed to position their fingers on the A, S, K, or L keys in preparation for the stimulus appearing in one of those 4 squares. Participants completed 8 practice and 40 test trials. The inter-stimulus interval varied randomly between 1 and 3 seconds. The measures of interest during the Choice RT block was RT on the correct trials. Figure 2 shows sample trials from the Simple RT and Choice RT blocks.

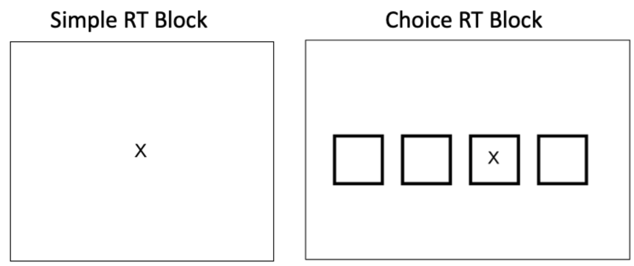

Figure 2: Screen shot of the Reaction Time task for the Simple and Choice reaction time blocks

Data Processing

Trials where participants did not respond or responded with the wrong key (for the choice RT block) were labelled as incorrect and omitted from data analysis. Trials where participants were incorrect were removed since it is hard to determine the factors responsible for the reaction time on incorrect responses. In total, approximately 4.5% of the data was removed from any further analysis. Potential outliers on the lower bound were detected using a strategy to exclude trials where RT was less than 100ms.

Data Analysis

The ex-Gaussian distribution was used to estimate parameters from each individual's RT data. The probability density function (PDF) of Ex-Gaussian distribution with three parameters can be expressed as shown in Equation 1:

$$p(x) = \frac{1}{\tau}\exp(-\frac{x}{\tau} - \frac{\mu}{\tau} - \frac{\sigma^2}{2\tau^2})\, \Phi(\frac{x-\mu-\sigma^2/\tau}{\sigma}) \qquad (1)$$

where μ and σ are the Gaussian mean and standard deviation, respectively. τ is the exponential rate parameter, and Φ is a standard normal cumulative distribution function (Zandt, 2002). As can be noted, for $\tau = 0$, the PDF in Equation 1 becomes a Gaussian PDF with no skew. τ is positive for positive skewness in the data and converse.

Differences in mean reaction time and the ex-Gaussian parameter averages between the VGP and nVGP groups were compared using the Mann-Whitney test, the non-parametric alternative to the independent samples t-test. The Bonferroni correction was applied to correct for multiple comparisons. As an additional test, Bayesian t-tests were conducted using JASP (JASP Team, 2020) to compare the two groups on the aforementioned variables to quantitatively support or disprove our hypothesis.

Results

The primary question was whether there would be differences in performance on the Reaction Time task between the VGP and the nVGP groups.

Group Level Analysis

Mean RT for the VGP group was significantly less than the mean RT for the nVGP group, U = 123,374, $p < .001$, r_{pb} = .26 for the Simple RT block.

Mean RT for the VGP group was significantly less than the RT for the nVGP group, U = 381,276, $p < .001$, r_{pb} = .37 for the Choice RT block. It appeared that the critical difference between the two groups (α = .0063 corrected for the number of tests) was still significant for Simple Mean RT and Chioce Mean RT.

Table 1 shows a summary of the descriptive statistics for the mean. Figure 3 shows the mean RT distributions for the Simple RT and Choice RT blocks. For a more detailed comparison, the RT distributions for the two groups are shown in Figure 4 and Figure 5.

Table 1: Summary of mean reaction time in milliseconds for VGP and nVGP groups with Bayes factor (BF) values shown. H_0: VGP = nVGP and H_1: VGP<nVGP

Measure	VGP **(n = 22)**	nVGP **n= 37)**	BF_{10}
Simple RT			
Mean (SD)	260 (59)	283 (82)**	11,006
Choice RT			
Mean (SD)	395 (80)	446 (107)**	9.0e+12

** p < 0.001

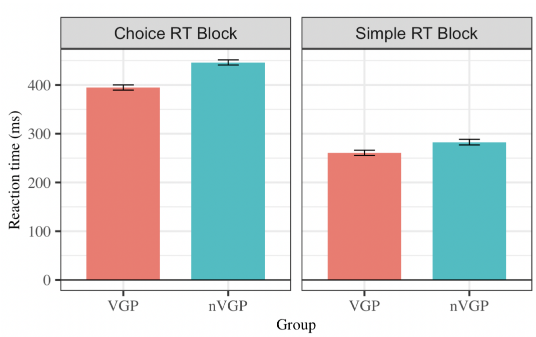

Figure 3: Performance differences for VGP and nVGP groups on the Simple RT and Choice RT blocks. Error bars represent 95% confidence intervals.

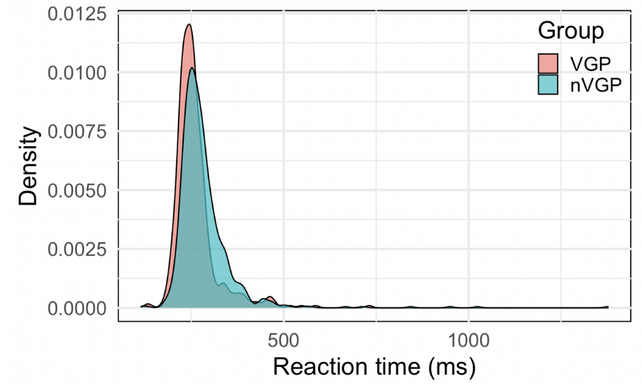

Figure 4: Display of the reaction time (RT) distributions for the VGP and nVGP groups on the Simple RT block.

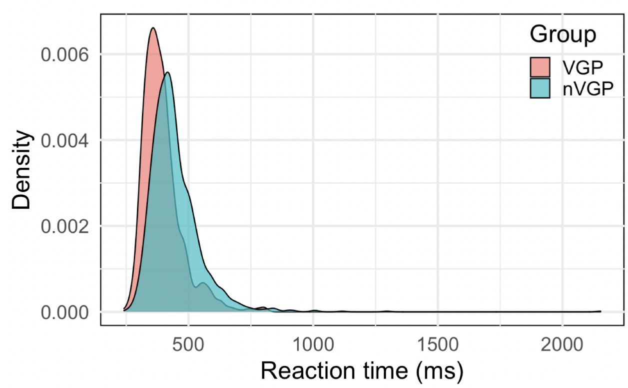

Figure 5: Display of the reaction time (RT) distributions for the VGP and nVGP groups on the Choice RT block.

Individual Level Analysis

For each participant, ex-Gaussian parameters were estimated and averaged for participants in the VGP and nVGP groups. For the Simple RT block, there were significant parameter differences between the VGP and nVGP groups for mu_{SRT} (p = 0.003, r_{pb} = .42) and $sigma_{SRT}$ (p = 0.004, r_{pb} = .41), but not for tau_{SRT} (p = 0.47, r_{pb} = .02). After applying the Bonferroni correction, the critical difference between the two groups was significant for mu_{SRT} and $sigma_{SRT}$.

For the Choice RT block, there were significant parameter differences between the VGP and nVGP groups for mu_{CRT} (p = 0.008, r_{pb} = .38) and tau_{CRT} ($p < .001$, r_{pb} = .53), but not for $sigma_{CRT}$ (p = 0.24, r_{pb} = .11). After applying the Bonferroni correction for the two groups, the critical difference between the two groups was only significant for tau_{CRT}. Table 2 shows a summary of the Bayes Factor values comparing the two groups on the ex-Gaussian parameters. Figure 6 shows the three ex-Gaussian parameters, averaged across participants within a group.

Table 2: Summary of ex-Gaussian parameters Mu, sigma, and tau for VGP and nVGP groups with Bayes factor values shown. H_0: VGP = nVGP and H_1: VGP<nVGP

Measure	VGP **(n = 22)**	nVGP **(n = 37)**	BF_{10}
Simple RT			
muSRT	221 (20)	239 (24)*	15.83
sigmaSRT	9 (9)	18 (16)*	6.46
tauSRT	39 (15)	42 (31)	0.40
Choice RT			
muCRT	356 (45)	379 (43)	2.51
sigmaCRT	29 (15)	32 (14)	0.53
tauCRT	38 (27)	66 (33)**	39.41

* $p < 0.05$
** $p < 0.001$

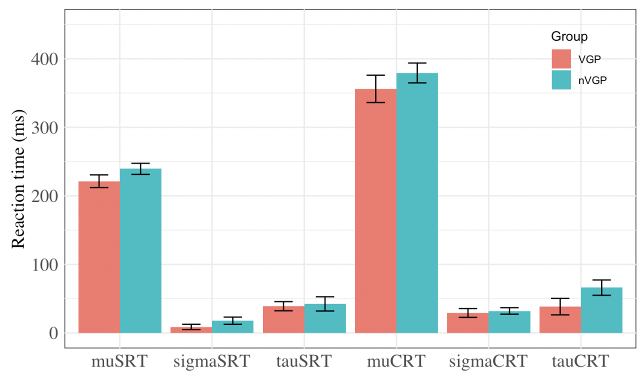

Figure 6: Ex-Gaussian parameters for VGP and nVGP groups on the Simple RT and Choice RT blocks. Error bars represent 95% confidence intervals.

Discussion

Using a Reaction Time task, we found robust differences in reaction time between the top-ranking Tetris players and novices. The Bayesian analysis supported the frequentist results and aided in the interpretation of these results.

The VGP group was significantly faster than the nVGP on the Simple RT block using the classic mean RT and the mu parameter from ex-Gaussian modeling. This confirms our hypothesis that Tetris expert players are faster at reacting to visual stimuli compared to novices. Existing research (Pardina-Torner et al., 2019; Dye et al., 2009) has also shown that VGPs exhibit faster RTs than nVGPs because VGPs are more advanced in producing a response once a stimulus is detected (Castel, Pratt, & Drummond, 2005). This necessary skill acquired by video game experts allows them to make decisions about the next move and act in response to that decision quickly.

For the Choice RT block, the VGP group was significantly faster than the nVGP using the classic mean RT. However, the non-significance of the mu parameter from ex-Gaussian modeling and the anecdotal evidence based on the Bayes Factor value suggests otherwise. When VGPs are presented with multiple choices, they become slower at responding than when presented with a single simple choice. They might be fast, but they are not consistently fast for different levels of task complexity.

The VGP group showed lower variability around the mean compared to the nVGP group (as indicated by sigma). The difference was significant for Simple RT but not for Choice RT. This suggests that top-ranking Tetris players may exhibit more consistent performance compared to novices in terms of their RTs deviating less from the mean. This might be attributed to different strategies used by the top-ranking players during Tetris that result in them being more likely to tap their controller at a consistent rate based on how each individual learns to finesse their game. However, for more complex tasks, such as the choice RT block, the VGP group does not behave as consistently.

There was evidence of a decrease in the skewness of the distribution for the VGP group compared to the nVGP group (as indicated by tau). As mentioned earlier, tau is positive for positive skewness in the data. The difference was significant for Choice RT but not for Simple RT. This suggests that there might have been an increase in the number of slower responses for the novices compared to the top-ranking players. Tau indicates abnormally slow responses (Gmehlin et al., 2014) which suggests that the novices had more lapses in attention compared to the top-ranking players. This is an area requiring further exploration and targeted research to understand why Tetris experts show an attention control advantage compared to novices and if this trend is consistent across video game players in general. Additionally, future research should further examine how reaction time and variability change for VGPs compared to nVGPs for different levels of task complexity, for example 1-choice vs 2-choice vs 4-choice reaction time tasks.

It would be interesting to compare expert Tetris players with experts of other video games such as League of Legends. While they are different types of games, it is worth examining the extent to which Tetris is associated with improvement in cognitive abilities such as reaction time compared to other types of video games.

Limitations

This study has two important limitations. First, there was a small sample size. The remote nature of this study meant that it was up to the participants to complete the study on their own time resulting in some attrition. We tried to account for these smaller sample sizes by using Bayesian analyses to quantitatively support or disprove the hypothesis. Future studies will recruit a wider sample of participants to provide support in favor of or against our hypotheses.

Secondly, this study was cross-sectional and considered populations on the two extremes of the video game expertise continuum. We cannot establish causality as there might be pre-existing differences in cognitive abilities that influence video game players to self-select and play video games. Thus, the faster reaction times and behavioral differences evident here might be attributed to other factors and experiences besides playing Tetris. This presents an interesting challenge and avenue for future research to consider and perhaps recruit from a wider participant pool to account for some of these pre-existing differences to examine intra-individual differences in cognitive abilities.

Future research could also design training intervention studies to establish causality and better understand the mechanisms behind transfer of cognitive abilities from Tetris to other tasks. Okagaki and Frensch (1994) trained non-gamers to play Tetris for 6 hr. The experimental and passive control groups completed tasks measuring spatial ability before and after the training intervention. Compared to a passive control group, the experimental group improved on the spatial ability tasks after training (Okagaki & Frensch, 1994). Contrary to these results, Sims and Mayer (2002) found no advantage of playing Tetris to improve spatial ability skills. It is hard to pinpoint the source of these inconsistencies especially since both studies used similar spatial ability tasks and the Sims and Mayer (2002) study trained non-gamers for a longer time (12 hr compared to 6 hr). Perhaps, there are pre-existing differences in cognitive abilities that would facilitate performance improvements of individuals in one group over another.

Conclusion

We have provided evidence suggesting that perhaps Tetris is more than just a puzzle game. It is a dynamic task with interacting perceptual and motor skill components that influence different cognitive processes such as mental speed. Using ex-Gaussian techniques, we were able to provide evidence to further support the growing literature that video game players do indeed exhibit faster reaction times compared to non-video gamers using the video game Tetris. We were also able to go beyond the mean and further show the inter-individual differences in variability and attention between the two groups. Such work has practical implications for the study of cognitive abilities in video game players and presents a methodology that has long been used to understand individual differences in reaction time (Heathcote et al., 1991), but has not yet been applied to the field of video gaming and cognitive abilities.

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