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Evaluation of Cognitive Control Using Non-Gaussian Reaction Time Distributions in Fractionated Executive Function Tasks

Dmitriy Kazakov
University of Wisconsin-Milwaukee

EVALUATION OF COGNITIVE CONTROL USING NON-GAUSSIAN REACTION TIME DISTRIBUTIONS IN FRACTIONATED EXECUTIVE FUNCTION TASKS

by

Dmitriy Kazakov

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ABSTRACT

EVALUATION OF COGNITIVE CONTROL USING NON-GAUSSIAN REACTION TIME DISTRIBUTIONS IN FRACTIONATED EXECUTIVE FUNCTION TASKS

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The University of Wisconsin-Milwaukee, 2019
Under the Supervision of Professor David C. Osmon, Ph.D., ABPP-CN

The present study seeks to further investigate and refine the three-factor model of executive function (EF; Inhibition, Shifting, and Monitoring/Updating) known as the unity/diversity framework (Miyake et al., 2000). Past work in this area utilized “power” tasks that prioritize accuracy and difficulty, but real-world problem-solving incentivizes quick and efficient solutions. Ten computerized reaction time (RT) tasks: four elementary cognitive tasks (ECTs; Jensen, 1987; Santos, 2016) with progressively increasing task demands and six EF tasks. The ratio scale of RT necessitated the use of non-Gaussian statistics to better describe distribution shape, while diffusion modeling (DM; Ratcliff, 1978) was used to interpret task complexity and performance. Generalized Regressions used ECT parameters to predict EF task parameters. DM analyses indicated Shifting was the most complex factor, followed by Monitoring/Updating, and Inhibition. Shifting and Monitoring/Updating were predicted by internal rule ECT parameters and non-executive-parameters, although the specific internal rule parameters were not unexpected. Inhibition was solely predicted by non-executive parameters, and almost exclusively choice RT. Within-task correlations between DM parameters were either positive or non-significant, save for the STOP-IT task, and not negative as expected. Overall, the present study demonstrated the utility of computerized RT tasks in evaluating EF, non-Gaussian parameters in

better describing RT data, and DM in interpreting task complexity. Investigating the efficiency aspect of EF offers an important complement to tradition “power” approaches to psychological measurement and represents an element of ecological validity that current widely-used measures lack.

To my grandfather Roman,

whose words echo to this day

<< Трудно в учобе, легко в бою >>

To my mother Dina

and grandmother Alla,

for all your support

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LIST OF ABBREVIATIONS

a	Boundary Separation (Diffusion Model parameter)
AIC-c	Akaike’s Information Criterion-corrected
ANOVA	Analysis of Variance
D-KEFS	Delis-Kaplan Executive Function System
DM	Diffusion Modeling
ECT	Elementary Cognitive Task
EF	Executive Function
IR	Internal Rule
KS	Kolmogorov-Smirnov
ms	Millisecond
RT	Reaction Time
SD	Standard Deviation
SSRT	Stop Signal Reaction Time
t0	Non-decision time (Diffusion Model parameter)
v	Drift Rate (Diffusion Model parameter)

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Evaluation of Cognitive Control using Non-Gaussian Reaction Time Distributions in Fractionated Executive Function Tasks

The aim of the present study is to investigate the executive nature of a series of reaction time (RT) tasks developed to provide a precise and systematic measure of cognitive speed and efficiency. Prior work in our lab (Santos, 2016) used the Miyake three-factor model for executive tasks, with variable results. That study suggested that two things: a) the "speed" and "power" aspects of cognition are confounded in executive function tasks, and b) analyzing the full RT distribution may provide more insight about these cognitive processes. The importance and utility of RT task design and rationale, as well as the prior study's results, will also be described. A more complete analytic strategy will be proposed that utilizes entire RT task distributions and explains how those distribution parameters can be used to elucidate the executive nature of RT tasks.

Executive Function

Executive function (EF) is an umbrella term for a wide range of higher-order psychological constructs that is among the most widely-researched topics in the field (Barkley, 2012). Although there is no singular operational definition available for this term, most researchers agree that it contains aspects of attention, self-regulation, planning, adaptation to novel circumstances, effortful and future goal-oriented, and control over lower-level processes (Anderson, 2002; Banich, 2009; Bianchi, 1895; Friedman et al., 2007; Gioia et al., 2000; Mahone et al., 2002). Some definitions also maintain that the goal of EF is to produce optimized and effective behavior (Baddeley, 1986; Robbins, 1996), introducing the critical aspect of *efficient* behavior in problem solving. Numerous studies have also demonstrated the variable impact of neurological and mental health conditions on EF factors (Damasio, 1994; Geurts, Verté, Oosterlaan, Roeyers, & Sergeant, 2004; Orellana & Slachevsky, 2013; Reitan & Wolfson, 1994; Shallice & Burgess, 1991; Snyder, 2013; Willcutt et al., 2001).

Although numerous theories of EF have emerged throughout the years, the unity/diversity framework (Miyake et al., 2000) is perhaps the most well-established on in use today. The three-factor model they proposed is comprised of set-shifting ("Shifting"), response inhibition ("Inhibition), and monitoring/updating ("Updating"), which are the most commonly researched and cited EFs in the literature and those most involved in cognitive control (Collette et al., 2005; Miyake & Friedman, 2012). Shifting is the ability to switch between one or more mental sets, or ways of interpreting and responding to information, based on the relevance of that mental set to the situation (Miyake et al., 2000; Monsell, 2003). Inhibition is the ability to deliberately stop the execution of either automatic or effortful responses (Friedman & Miyake, 2004; Logan, 1994; Miyake et al., 2000). Updating is the ability to store information in working memory, monitoring that store for task-relevant information, and updating that store with new information (Miyake et al., 2000; Sternberg, 1966). Latent variable analysis using multiple tasks for each EF found intercorrelations between factors ranging from .42 to .63 (Miyake et al., 2000), with established tasks providing loading on multiple factors. Multiple subsequent studies providing further support for the notion that EFs are neither unitary nor distinct (Fisk & Sharp, 2004; Friedman & Miyake, 2004; Friedman et al., 2006; Hull, Martin, Beier, Lane, & Hamilton, 2008; Miyake & Friedman, 2012). The three-factor model, then, provides a good framework to use when investigating EF tasks.

Reaction Time and Information Theory

Reaction time as a metric of cognitive processes has been a staple of psychological research since at least 1860s (Donders, 1869; Posner, 1978; Shepard & Metzler, 1971; Sternberg,

1966) and offers a slew of advantages over other measures, especially in EF research. RT operates on the ratio scale of measurement, having both a true zero point and equal interval distance, allowing for all possible mathematical operations and the direct measurement of a physical reality (i.e., time) rather than a developed scale (e.g., standard scores)(Jensen, 2006). The advent and current near-omnipresence of computers allows for an unprecedented level of precision in terms of stimulus presentation and RT recording at the trial level. RT by its very nature represents a measure of efficiency. Lezak's (1995) distinction of cognitive function as a measure of "how much was done?" and executive function as "how was it done?" rings true here. Because cognitive and physical processes necessarily take time to complete, a faster RT resulting in a correct response is more efficient, and therefore more optimized, than a slower one.

Jensen's (2006) body of work focused on mental chronometry, the measurement of cognitive process speed. The tasks he developed were termed elementary cognitive tasks (ECTs) and defined by Carroll (1993) to require a relatively small number of mental processes, a correct outcome, and successful outcome to be dependent upon using the instructions or the individual's sets/plans. Using terminology gleaned from information theory, one bit is defined as the amount of information needed to reduce uncertainty by half (e.g., a two-choice problem requires one bit to solve) (Shannon & Weaver, 1963). Hick's (1952) law is a mathematical explanation governing the amount of time necessary to make a response on a choice RT task as a function of the amount of information presented. It follows the formula $\log_2 n$, where n is defined as the number of choices offered. Using this model, Jensen (1987) found a linear increase in RT, approximately 27ms, progressing from 0-bit (1 option, $\log_2 1 = 0$) to 3-bit (8 options, $\log_2 8 = 3$) and explaining 97% of the variance in a college sample. While the RT increase is linear, the Hick's law formula is logarithmic due to half of the options needing to be eliminated per step until the solution is apparent. This allows for the operationalization of task difficulty, wherein tasks are rated by bits, as each bit of information increases the amount of time to respond. This also allows for two additional things to occur in the context of EF task development. One is the quantification of internal rules (IRs), which are the hallmark of EF tasks and are what distinguish them from solely perceptual-motor tasks (e.g., 0-bit simple RT). The other is the ability to create a systematic hierarchical design of RT tasks starting from the most basic to increasingly complex using the same set of stimuli where constructs can be added one at a time. Therefore, the impact of adding a particular construct or rule can be evaluated in terms of how much of an RT increase it yields.

While the development of this framework is useful, the introduction of executive tasks complicates things in terms the expected RT increases according to Hick's law. Introducing an IR, or a set of instructions that govern task-specific behavior that must be successfully internalized to successfully complete it, would increase uncertainty. The tasks used by Jensen were choice RT tasks, but did not utilize IRs that persist throughout the task (Jensen, 1987; Jensen & Munro, 1979). Therefore, RT would most likely increase as a result of an IR, but the increase would be unlikely to be linear.

ECTs and the Miyake Model

Four ECTs were developed by our lab in a systematic and hierarchical fashion to attempt to measure these RT increases. The first two tasks were non-executive, direct-response tasks that involved pressing a button when a stimulus was presented (0-bit simple RT) or pressing the response button on the same side as a presented stimulus (1-bit choice RT; left or right). The other two tasks were 1-bit and 2-bit IR tasks using the same stimulus set as the first two tasks. For the 1-bit executive task, the IR was to always make a response using the button on the side opposite to where the stimulus was presented. The executive aspect of this task was to consciously alter the prepotent response of a same-side response into the opposite response. The 2-bit executive task went further by asking participants to alternate between a same-side response (a la the 1-bit non-executive task) and an opposite-side response (a la the 1-bit executive task) on each trial. In addition to requiring the alteration of prepotent responses on opposite-side trials, it also requires the ability to keep track of the trial type by referring to the previous trial's type (i.e., same-side or opposite-side) and use the proper response set. While the stimuli used in these tasks are visual, the paradigm could technically be easily adapted into other modalities to accommodate individual circumstances.

Raw data from preliminary and unpublished studies from our lab replicated previous work (Hick, 1952, Jensen, 1987; Jensen & Munro, 1979), finding non-executive RT task performance increases approximately 27ms from 0 to 1 bit (Santos, 2014; Santos & Osmon, 2012a; Santos et al., 2014, 2015). However, a nonlinear RT increase was found when comparing non-executive and executive tasks performance. Interestingly, this pattern is not affected by cultural factors or the order in which the tasks are taken (Santos & Osmon, 2012b; Santos, Cadavid, Giese, Londono, & Osmon, 2013a; Santos, Park, Kennedy, Giese, & Osmon, 2013b). The nonlinear increase indicates that the executive tasks and their demands are indeed different from those of the non-executive tasks.

Miyake et al.'s (2000) investigation of some popular standalone EF measures (e.g., Wisconsin Card Sorting Test, Tower of Hanoi) posed the question of whether other established EF measures could stand the same scrutiny. Santos (2016) sought to apply the three-factor model to several subtests from the Delis-Kaplan Executive Function System (D-KEFS; Delis, Kaplan, & Kramer, 2001) and the four-ECT series. He found a 22ms increase between simple and choice

RT performance, a 56ms increase between choice RT and 1-bit IR, and a 533ms increase between 1-bit and 2-bit IR; a clearly nonlinear RT function. A linear fit of the ECT data only accounted for close to 60% of the variance, but adding a quadratic component resulted in a better fit, explaining 82% of the variance. If 2-bit IR performance was broken down into quartiles, a linear fit explained 86% of the variance, while adding a quadratic term improved it to 94%. Factor analysis revealed the presence of three factors in the D-KEFS data, with Verbal Fluency loading onto Updating, Color-Word Interference loading onto Inhibition, and Sorting loading onto Shifting. Overall, faster RT performance on the ECTs was associated with better D-KEFS scores. Both simple and choice RT performance correlated significantly with Inhibition and Updating (Pearson's r -.25 to -.31), but not Shifting. The 1-bit IR task only correlated significantly with Inhibition (r = -.33). The 2-bit IR task correlated significantly with Inhibition (r = -.44) and Shifting (r = -.24), but not Updating. Hierarchical multiple regression was performed, entering Updating in the first step to control for working memory, followed by Inhibition and Shifting together in the second step. This model explained 12.5% of the simple RT task variance, 14.3% of choice RT variance, 13.4% for 1-bit IR variance, and 22.7% of 2-bit IR variance. Inhibition yielded the highest beta weights across all ECTs. Secondary contribution came in the form of Updating for simple RT, Shifting for both IR tasks, and Updating followed by Shifting for choice RT.

To put the results into perspective, the ECT tasks performed as expected and the D-KEFS tasks conformed to the three-factor Miyake model. D-KEFS scores were predicted to more strongly correlate with IR tasks due to their executive nature, but the results were variable. Inhibition was a ubiquitous factor, but updating was only related to non-executive tasks, while Shifting was only related to the most difficult ECT. While these results provide some support for the unity/diversity framework (Miyake et al., 2000), the amount of variance explained by the regression model leaves a lot to be desired.

Re-evaluation and Refinement of the Miyake Model Approach

Test development has long wrestled with the issue of speed versus power (Kelley, 1927) in regard to whether they were equivalent in cognitive testing and whether they should be controlled. Speed and power have at most a moderate negative correlation (r = -.4), but load on different factors (Sheppard & Vernon, 2008), even when the same test is given with or without a time limit (Carroll, 1993; Davidson & Carroll, 1945; Lord, 1956). The power/accuracy category usually includes tests of intelligence or cognitive ability that are looking for an upper limit, similar to Lezak's (1995) view of the term *cognitive function*. The D-KEFS tasks, like many modern clinical assessments, are a mix of power and speed because they implement some time limitations, however, they are considered primarily power measures because of the strong emphasis on accuracy. Of the three D-KEFS measures used in the Santos (2016) study, the Color-Word Interference task would be considered more of a speed task over the others, but this is solely due to time-on-task limitations and due to trial RT. Still, it is the only one that correlates significantly with all four ECTs. In a recent survey of practicing neuropsychologists, the fourteen most frequently used assessments are all power measures, but incorporate some sort of timed measures by either noting or limiting time-to-completion (Rabin, Paolillo, & Barr, 2016). However, they do not utilize millisecond RT recording, the precision of which is critical to the definition of a speed task.

Clearly, there was a need to refine the tasks chosen to represent the three factors of the Miyake model. The ECT tasks, even with the demonstrated increase in difficulty across tasks, were a series of speed tasks. The D-KEFS, being a collection of power tasks with some speed component, would provide a poor comparison to the ECTs for the goal of obtaining evidence of concurrent validity. Even looking at the experimental tasks used that comprise the three factors in the Miyake et al. (2000) study, only four of the nine tasks (1 Inhibition, 3 Shifting) used a dependent measure based in RT and not solely accuracy. RTs for some tasks (e.g., plus-minus task) were recorded using a stopwatch, and some tasks barely have a speed component (e.g., keep-track). Therefore, even the exact tasks used in the Miyake study would not make for a good comparison against ECTs under this framework.

To address these limitations, a completely new approach was devised for the present study. Six new computerized tasks, two for each factor, were developed with Carroll's (1993) intentions for ECTs and speed tasks in mind. That is, they are easy to understand, involve relatively few processes (with care taken to prevent construct overlap as much as possible), and relatively easy to complete given the need for fast responding. Operating strictly on a speed level creates some complications, as well. RT tasks require large numbers of trials to obtain a reliable estimate of cognitive speed, leading to longer overall completion times for what looks to be a simple task on the surface. Long, simple tasks can sometimes lead subjects to boredom and attentional lapses, which are reflected in RTs. The frequency of these lapses is actually quite telling about individual attention, so this occurrence is more informative than damaging (McVay & Kane, 2012). Additionally, because the focus is on speed, item difficulty within a task must be kept constant. Any increase in difficulty would necessitate a new sub-task with its own series of trials to ensure that recorded RTs reflect a single set of instructions.

Another fundamental change was to depart from using normal distributions for RT. Santos (2016) excluded trial RTs that were more than 2 SD greater than the mean and transformed his RT data into a normal distribution. RT most often does not follow a Gaussian distribution and forcing RT data into a normal distribution could also lead to incorrect inferences being drawn because of Gaussian assumptions (Ratcliff, 1993). Not using the full RT distribution can also lead to missing critical patterns during interpretation (Noorani & Carpenter, 2011). Therefore, it does not follow to use Gaussian distribution statistics with data that is inherently non-Gaussian to begin with.

Reaction Time Distributions and Diffusion Modeling

RT is one of the rare psychological phenomena that do not conform to a normal distribution. Part of this has to do with its physical nature; it can only be positive and has no maximum value. In terms of distribution shape, this result in a positive skew, or “fat tail,” that may reflect attentional lapses due to loss of set, or mind-wandering associated with lack of engagement. In fact, depending on a variety of intraindividual and task factors, the reaction time distribution could vary from near-normal to remarkably non-normal (Ratcliff, 1993). Some examples include ex-Gaussian (a combination of Gaussian and exponential; Burbeck & Luce, 1982), shifted Wald (positively-skewed unimodal distribution fully shifted away from the zero-point; Matzke & Wagenmakers, 2009), and normal-X mixtures (multiple normal distributions), among others. Luce’s (1986) work suggested that ex-Gaussian is typically the best-fitting distribution for RT data, but this assumption is not always correct and requires an analysis of individual trial data, not just group patterns.

The role of fitting a distribution cannot be understated when working with this kind of data. A normal distribution offers two main parameters: mean and standard deviation (SD), which is all that is really needed if the scores are evenly distributed around a central point. Ex-Gaussian distributions instead have three components: mu, sigma, and tau. Mu and sigma represent the mean and SD of the Gaussian portion of the distribution. Tau, however, describes both the mean and SD of the exponential portion. Because of the difference in shape between RT and normal distributions, the normal Gaussian parameters and mu and tau would not match up when calculated using the same data set. Thus, selecting a distribution that poorly fits the data results in parameters that poorly describe the data, ultimately leading to incorrect conclusions being made about the data. In essence, proper distribution-fitting provides the most valid information regarding natural phenomena, which is critical to good scientific practice. Several recent studies have shown the superiority of using ex-Gaussian distributions over normal ones in RT tasks involving attention (Keiffaber et al., 2006; Leth-Steensen et al., 2000; Matzke, Dolan, Logan, Brown, & Wagenmakers, 2013; Osmon, Kazakov, Santos, & Kassel, 2018).

While ex-Gaussian distribution-fitting for RT data is important, it unfortunately lacks underlying theoretical support and cannot account for the mechanisms that drive performance (Heathcote, Popiel, & Mewhort, 1991; Luce, 1986; Matzke & Wagenmakers, 2009). This has caused some debate about whether ex-Gaussian distribution parameters should be interpreted. The Gaussian component has been interpreted as involving more stimulus-driven, sensorimotor, and automatic processes, while the exponential component has been described as involving attention-demanding, intentional, and decisional processing (Balota & Spieler, 1999; Gordon & Carson, 1990; Keiffaber et al., 2006; Rohrer & Wixted, 1994; Rotello & Zeng, 2008). Those who are more conservative and refuse to interpret the parameters instead use them to evaluate competing cognitive models (Heathcote et al., 1991; Ratcliff, 1978, 1993; Ratcliff & Murdock, 1976). Even though proportionately few RTs occupy the tail-end of the distribution, their contribution to the shape and understanding of a distribution is still of note. Therefore, while the ex-Gaussian distribution can describe RT with high accuracy, a lack of theoretical backing precludes its more widespread practical use.

Fortunately, there is an alternate method for interpreting non-Gaussian data in the form of diffusion modeling (DM). Ratcliff's (1978, 1993, 2013) diffusion model is an approach to complexity and information gathering that works particularly well with RT data, but only on tasks that have a binary outcome. Individual trial RT data is used to estimate decisional (i.e., cognitive processing) and non-decisional (e.g., encoding, response execution) time parameters. Data from both correct and incorrect response trials are used in the model in order to make inferences about those outcomes and the task as a whole. While most RT tasks are designed to be relatively error free, the presence of errors can be helpful, and actually helps inform the analysis that a diffusion model can produce.

One parameter is threshold separation (*a*), which refers to the distance between two outcomes. Greater task difficulty is usually associated with larger separation (Voss, Rothermund, & Voss, 2004). Drift rate (*v*) is also critical, as it represents the average slope of the speed and direction of information accumulation over time. Drift rate is also related to task complexity, in that easier tasks have a greater absolute drift rate (i.e., shorter distance from trial start to trial end)(Voss et al., 2004). Its utility with RT data in healthy clinical populations, both child and adult, is also well-documented (Mulder et al., 2010; Ratcliff & van Dongen, 2011; Spaniol, Madden, & Voss, 2006; Wagenmakers, Ratcliff, Gomez, & McKoon, 2008; White, Ratcliff, Vasey, & McKoon, 2010; Zeguers et al., 2011). Non-decision time (*t0*) is the average duration of non-decisional processes (e.g., encoding and response execution) is not a primary measure of task complexity, but separating it out from decision-process parameters can be helpful in better understanding a task.

The amount and variety of evidence for this model indicate greater theoretical support for its continued use and a stronger rationale for its parameters and what they represent. Therefore, the addition of the diffusion model to the study bolsters the theoretical support for the use of ex-Gaussian distributions with RT. Essentially, ex-Gaussian distribution parameters will be used to broadly describe RT data, being more valid than normal parameters, and diffusion model parameters will be used to interpret the data and draw conclusions about the cognitive tasks.

The Present Study

The present study seeks to further investigate and refine the three-factor model of executive function known as the unity/diversity framework (Miyake et al., 2000). Past work using a series of systematic and hierarchical elementary cognitive tasks to obtain concurrent validity using D-KEFS tasks found variable relationships between factors and RT performance due to (a) a mismatch between task types vis-à-vis the speed/power taxonomy and (b) using truncated RT distributions and Gaussian distribution statistics (Santos, 2016). A new suite of computerized executive RT tasks were developed for each EF factor that were based on speed. This study utilized full RT distributions and ex-Gaussian distribution-fitting, being the preferred and most empirically valid methodology for RT data. Diffusion modeling provides much-needed theoretical support for non-Gaussian data and was used to interpret task performance. In summary, this is an investigation of EF using a combination of sophisticated RT tasks and statistical methodology whose aim is to address design shortcomings and improve the way EF is assessed in the future.

Hypotheses

1. Non-Gaussian parameters of IR ECTs will predict non-Gaussian parameters of EF tasks, while non-executive ECT parameters are not expected to contribute to predictive models. The tasks used to represent the EF factors in both the Miyake et al. (2000) and Santos (2016) studies were primarily power tasks, which yielded confusing results. Using only speed tasks

designed to only tap one EF construct at a time should allow for improved comparison between tasks and more easily draw divisions between task types.

2. The Shifting factor will be predicted by non-Gaussian parameters of the 2-bit IR ECT.

3. The Monitoring/Updating factor will be predicted by non-Gaussian parameters of the 1-bit IR ECT.

4. The Inhibition factor will be predicted by non-Gaussian parameters from all four ECTs. However, the strongest predictors are expected to be from the IR ECTs.

Replicating Hypotheses 2 and 4 would be consistent with Santos (2016), while the improved task design should allow for Monitoring/Updating to be properly represented in the IR tasks.

5. EF tasks that are predicted by non-Gaussian IR ECT parameters will have greater threshold separations and slower drift rates. Both parameters reflect task complexity, therefore, more complex EF tasks should relate more closely to the executive nature of the IR ECTs. Tasks associated more with non-executive ECTs, which are easier to complete, are more likely to have lower task complexity.

6. Shifting tasks will have greater task complexity than Monitoring/Updating tasks, and Monitoring/Updating tasks will have greater task complexity than Inhibition tasks.

Methods

Participants

A sample of 46 undergraduate students from the University of Wisconsin-Milwaukee was recruited through an online department subject pool (SONA). Informed consent was obtained after describing the experiment, the tasks involved, and any risks associated with participation. Participants must be at least 18 years old and be proficient in English to ensure comprehension of task instructions. Participants without normal or "corrected-to-normal" vision were excluded from the study. Three participants were excluded from the study due to self-discontinuing the study or due to technical issues resulting in limited usable data. Participants were debriefed following their completion of the study. All participants were compensated with course credit.

The final sample consisted of 43 participants. The sample consisted of 35 females (81.4%) and 8 males (18.6%). The average age of the participants was 21.88 years (*SD* = 3.32), while the median age was 21. The sample's race/ethnicity distribution was as follows: 51.16% White (n = 22), 16.27% Black/African-American (n = 7), 13.95% Hispanic/Latinx (n = 6), 6.98% Asian/Pacific Islander (n = 3), 6.98% Middle-Eastern (n = 3), and 4.65% Native American/Alaska Native (n = 2). Thirty-four participants were as right-handed, six as left-handed, and three as ambidextrous.

Materials

Equipment. All computerized tasks were administered using a Windows-based computer with a standard keyboard, mouse, and color monitor. All computerized tasks, with the exception of one standalone third-party program (i.e., STOP-IT), were developed with and will be administered using DirectRT v2016 (Empirisoft, 2016). DirectRT is a proprietary psychology experiment software that utilizes a computer's DirectX software to access the processor clock, allowing for precise control over stimulus timing and event recording at the scale of 1ms.

Demographic data. After obtaining consent and before starting the cognitive tasks, a research assistant asked the participant a series of common demographic questions. After that, the research assistant completed a brief neurodevelopmental interview consisting of questions about the mental health and medical history of the participant and their immediate family. Participants are not excluded based on this information. Participants were free to refuse to provide information about their own and/or their immediate family's psychological history without being excluded from the study. All of this data was recorded on a participant summary sheet (see Appendix A).

Shifting tasks.

Number-letter task (NL). In this three-block task, a number-letter pair appears in one of the four quadrants of the screen. In the first block, pairs appear only in the top half of the screen, and participants respond via button press whether the number in the number-letter pair was even or odd. In the second block, pairs appear only in the bottom half of the screen, and participants respond about whether the letter in the number-letter pair was a vowel or a consonant. Finally, in the third block, number-letter pairs randomly appear across all four quadrants. This time, participants must utilize the rules from both previous blocks. Each block was preceded by eight practice trials. The first two blocks have 32 trials each, while the third block has 128 trials. Half of the third block's trials are shift trials, where the participant must switch their response set from odd/even to vowel/consonant, or vice versa. A shift cost can be calculated by subtracting the average RT from the first two blocks from the average shift trial RT. Miyake et al. (2000) used a modified version of the number-letter task used by Rogers and Monsell (1995). The third block in the Miyake study's version of this task had the number-letter pairs' location change in a clockwise progression throughout the block. Over the course of 128 trials, it is not unlikely that a participant may begin to learn the pattern and anticipate the location of the next trial's pair. For this reason, pair location was randomized throughout, with some switch trials occurring consecutively.

Color-shape task (CS). In this task, participants are presented with a shape (circle or triangle) inside of a colored rectangle (red or green). A cue letter (C or S) is presented above the rectangle and determines the trial's response set. If the letter is C, the participant must respond via button press about whether the color inside the rectangle is red or green. If the letter is S, they must respond about whether the shape inside the rectangle is a circle or a triangle. There are six practice trials with feedback, followed by two test blocks of 48 trials each. Half of the trials in each test block are shift trials, in which the response set to be used is different from the one in the previous trial. This task was previously developed by Miyake, Emerson, Padilla, and Ahn, (2004) and is commonly used as one of the group's shifting tasks (Friedman et al., 2008).

Monitoring/updating tasks.

Sternberg memory scanning task (SMS). The Sternberg (1966) memory scanning task is one of the earliest examples of the experimental evaluation of working memory. In this task, strings of numbers ranging from one to six digits are presented serially for 1200ms per digit. An asterisk signals the end of the string, followed by a numerical probe that was part of the string in 50% of trials. The task will have two 48-trial blocks, with the participant responding after each trial whether the probe was or was not in the sequence. Although some versions of this task exist wherein the entire string is presented simultaneously, this would theoretically only measure memory scanning, and not updating of information. Therefore, a serial presentation is optimal for this study, despite taking significantly more time to complete.

Piek updating task (PU). Piek et al. (2004) describe their "trailmaking/memory updating task" as a version of Rabbitt's (1997) task that is simplified for children. In this task, letters appear on the screen one at a time and require a response to be made regarding whether the letter is a target. The target set includes letters A through D, although the specific target rotates through the set with each trial. For example, A is the target for the first trial, B for the second, and so on, with the target rotating back to A for the fifth trial. Piek et al.'s (2004) version had two 120-trial blocks, with only 20 target trials in each block (16.7%). Some modifications were made to this task for the present study. Firstly, only one 120-trial block is used. Second, the number of target trials were increased to 40% (48 of 120). Third, the task will display a reminder, displayed for 5s, every 12 trials that the target will rotate back to A for the next trial. This was introduced as a way to prevent participants from spoiling all remaining responses in the task if they happen to make an early mistake.

Inhibition tasks.

Modified Stroop task. The Stroop task (Golden, 1978; Stroop, 1935) is a classic inhibition task, but was originally made as a paper-and-pencil verbal task. The modified computerized version used in this study utilizes a set number of trials rather than a time limit like the original. Stimuli are presented one at a time and remain on the screen until a response is made. Instead of the word trial, there is a 50-trial block where the participant is presented with a color word (i.e., red, blue, or green) in black ink, and must make the appropriate button response based on the color. The color block also has 50 trials, each of which presents a series of asterisks in one of the three colors, which must be responded to with the same button press scheme as before. The color-word aspect of the task in this study is significantly different from those in other Stroop-like tasks. To measure inhibition in more detail, we incorporated the use of positive and negative priming trials throughout the block. In this task, negative priming would be in effect when the inhibited response for one trial becomes the correct response on the next trial. For example, blue in red ink (blue inhibited, red correct) is followed by green in blue ink (green inhibited, blue correct). Pulling for a previously inhibited response is more cognitively taxing and results in slower RTs. Positive priming instead involves calling for the same correct response on two consecutive trials. Because the response has just been activated, a second trial that requires the same response would yield faster RTs. The color-word block has 72 trials in which a color word is presented in an ink color different from the color of the word itself (e.g., “red” in blue ink), and the participant’s response must match the color of the ink rather than the printed word. There are 18 positive priming and 18 negative priming trials, along with 36 neutral trials that occur before each priming trial to “reset” the participant’s priming. In order to accomplish this, all priming trials display the printed word “yellow” in an ink color consistent with the priming for that trial, while the color yellow was never used. Neutral trials are the only trials to actually display printed words in one of the three main colors. Using this approach, it is possible to calculate separate RTs for negative, neutral, and positive priming, which should allow for an individual assessment of inhibition sensitivity.

STOP-IT task. STOP-IT is a standalone computerized task using the stop-signal paradigm of response inhibition (Verbruggen, Logan, & Stevens, 2008). While the paradigm itself is many decades old (Lappin & Eriksen, 1966; Vince, 1948), significant developments have been made in terms of theoretical understanding and technological achievement (Logan & Cowan, 1984; Logan, 1994; Logan, Schachar, & Tannock, 1997). The paradigm deals with one of the fundamental questions in reaction time literature, which is how to measure RT for an inhibited response (i.e., one that is successfully withheld from occurring and therefore does not technically exist). The task consists of two 64-block trials where participants are presented with either a circle or a square in the center of the screen and must press the corresponding response button as quickly and as accurately as they can. On 25% of trials, a 75ms 750 Hz stop signal tone will play after display onset that will indicate that the participant is to inhibit their response. On the first of these stop trials, the tone occurs 250ms following display onset. Successfully inhibiting a response will cause the tone to play 50ms further into the trial, while unsuccessfully inhibiting a response will move the tone 50ms closer to the display onset. Successful inhibition results in longer delays, making it more difficult or even impossible to stop an in-progress response that occurs as the tone is played. The goal of this procedure is to identify the stop signal delay at which the participant is likely to inhibit their response 50% of the time. This individual stop signal delay is then subtracted from the participant's average RT on no-signal trials to obtain their stop signal RT, which provides a reliable estimate of how long it takes them to inhibit a response.

Elementary cognitive tasks (ECTs). The ECTs, as extensively discussed, are a series of four 120-trial tasks of increasing difficulty. All four tasks in the series are based on Jensen's (2006) ECT paradigm and their current version was developed by Santos (2014). The first task, named the "0-bit" task, simple RT task that involves pressing a button each time a large dot appears on the screen. The second task, the "1-bit non-executive" task, involves pressing the left response key when the dot is on the left and the right key when the dot is on the right. The third task, the "1-bit IR" task, is identical to the 1-bit non-executive task, with the exception of the response set being reversed (i.e., pressing the right key if the dot appears on the left). For the fourth and final task, the "2-bit IR" task, the response set alternates between the two 1-bit tasks with each trial (i.e., the first trial calls for a "same side" response, while the next trial calls for an "opposite side" response).

Procedure

After informed consent is obtained, a research assistant conducted a brief demographic interview, as described above. Following that, the research assistant guided the participant through the battery of computerized and paper-and-pencil tests described above. Although the instructions for each task were presented visually on the screen, the research assistant always read the directions to the participant and provided feedback during practice blocks to ensure participant comprehension. This was to improve our ability to say that an individual's poor performance was reflective of actual ability rather than lack of comprehension. The demographic form was free of identifying information, and no coding sheet was kept to link participant names to their demographic forms. At the end of the study, the participants were debriefed. A complete study session lasted approximately 1.5 hours.

Data Analysis

Initial data analysis to obtain Gaussian distribution statistics were performed using Microsoft Excel, as DirectRT outputs raw data and summary sheets in a compatible format. Excel was used for calculating accuracy, mean RT and RTSD (both overall and per sub-task), as well as shift cost for shifting tasks. RT distributions were kept intact, although trial RTs faster than 150ms, the physiological limit of physical response, were excluded. Gaussian statistics are reported for comparison, but were not analyzed.

JMP (SAS, 2015a, 2015b) was used to identify the best-fit distribution for each task's raw RT data using the Akaike's Information Criterion-corrected (AIC-c; SAS, 2015b). AIC-c values of distributions with 2 points of each other are considered of comparably equal fit, while those within 3-4 points of each other are considered possible, but less likely fits. Although ex-Gaussian appears to be the preferred RT distribution, this is not always the case. Therefore, these analyses will help determine which distribution type certain task types tend to favor. In order to validate the executive nature of the ECTs, their ability to predict Miyake EF factors must be investigated. As the parameters themselves are not normal by nature, Generalized Regression was used to predict each non-Gaussian EF factor parameter (Mu, Sigma, Tau) using non-Gaussian ECT parameters. Subsequently, group DM parameters (*a*, *v*, *t0*) were used to predict the non-Gaussian parameters that were most contributory to the initial model.

Diffusion model (Ratcliffe, 1978) analyses were conducted for all EF and ECT tasks (except 0-bit simple RT) in order to gain a better theoretical understanding of their complexity. Raw RT data was analyzed using fast-dm (Voss & Voss, 2007) to obtain threshold separation and drift rate values. Non-decision time (*t0*), or the average duration of non-decisional processes (e.g., encoding and response execution) will also be reported. Although the program offers several parameter estimation methods, Kolmogorov-Smirnov (KS; Kolmogorov, 1941) was used in all cases. This is the preferred method of the fast-dm developers, as it offers the best optimization and provides the best model fit (Voss et al., 2004; Voss & Voss, 2007).

SPSS v23 (IBM Corp., 2015) was used to perform one-way repeated-measures analyses of variance (ANOVAs), post-hoc paired *t*-tests, and bivariate Pearson correlations on non-Gaussian and diffusion model data. ANOVAs and follow-up comparisons were used to determine the relationships between ECTs and executive tasks/factors.

Results

Non-Gaussian Statistics

Gaussian and non-Gaussian statistics for the four ECTs and six executive tasks are presented in Tables 1-7. Mean accuracy and RT for specific trial types are also provided, where applicable. Switch cost is provided for shifting tasks. As this study focused on non-Gaussian parameters, Gaussian data was not analyzed and is provided for informational purposes only.

All tasks were subjected to group distributional analyses comparing the fit of all tasks according to AIC-c values across the following distributions: ex-Gaussian, LogNormal, Gamma, GLog, Normal-2 Mixture, Normal-3 Mixture, Weibull, Extreme Value, and Exponential. The following tasks best fit an ex-Gaussian distribution: 2-bit IR, CS, NL, PU, SMS, and Stroop. The following tasks best fit the Normal-3 Mixture distribution: 0-bit, 1-bit, 1-bit IR, STOP-IT. Group distributions were quite different than individual participant distributions; no tasks fit the group distribution for a majority of individual participants, although individual participants fit the group distribution with the greatest frequency than any other distribution.

Shifting Factor.

Shifting Mu. Shifting Mu was normally distributed and an Adaptive Elastic Net Generalized Regression with normal distribution model was utilized. Model fit was $R^2 = .34$ and one variable, 1-bit IR Mu, significantly contributed to the model. DM parameters did not predict 1-bit IR Mu.

Shifting Sigma. Shifting Sigma was distributed according to a Weibull distribution and an Adaptive Elastic Net Generalized Regression with Weibull distribution model was utilized. Model fit was $R^2 = .17$ and one variable, 1-bit IR Mu, significantly contributed to the model. Shift Mu and Shift Sigma correlate at $r = .74$. DM parameters did not predict 1-bit IR Mu.

Shifting Tau. Shifting Tau was LogNormal distributed and an Adaptive Elastic Net Generalized Regression with LogNormal distribution model was utilized. Model fit was $R^2 = .39$ and three variables, 0-bit Sigma; 0-bit Mu; and 0-bit Tau, significantly contributed to the model. Greater Shifting Tau was associated with simple mental speed but in a complex fashion. Specifically, greater (i.e., slower) extreme RTs in the Shifting tasks were associated with speedy efficient RTs and greater variability of speedy efficient RTs, *but also* extremely long RTs.

To further explore these complex relationships and how each predictor contributed, Generalized Regressions were run to predict each ECT variable from DM parameters (a, v, $t0$). 0-bit Mu was predicted utilizing a LogNormal distribution modeled Adaptive Elastic Net ($R^2 = .90$) with only non-decision time contributing significantly, indicating that 0-bit Mu is most related to non-decision-making mental speed but not boundary separation or drift rate parameters. 0-bit Sigma was evaluated with a LogNormal model ($R^2 = .52$) with both non-decision time and boundary separation contributing significantly, with more 0-bit variability being associated with slower non-decision-making mental speed and a higher boundary separation. 0-bit Tau was evaluated with a LogNormal model ($R^2 = .74$) with only drift rate contributing significantly and more extremely long 0-bit RTs being associated with slower information accumulation.

Monitoring/Updating Factor

Monitoring/Updating Mu. Monitoring/Updating Mu was normally distributed and an Adaptive Elastic Net Generalized Regression with normal distribution model was utilized. Model fit was $R^2 = .43$ and two variables, 2-bit IR Mu and 1-bit Mu, significantly contributed to the model. DM parameters did not predict 2-bit IR Mu, but did predict 1-bit Mu ($R^2 = .29$) with slower 1-bit Mu being related to slower non-decision time and higher boundary separation. These results indicate that efficient RTs for Monitoring/Updating relate to efficient complex internal rule RTs and efficient choice RTs that derive from quick basic RT, but conservative decision-making.

Monitoring/Updating Sigma. Monitoring/Updating Sigma was normally distributed and an Adaptive Elastic Net Generalized Regression with normal distribution model was utilized. Model fit was $R^2 = .36$ and one variable, 1-bit Mu, significantly contributed to the model. Boundary separation predicted 1-bit Mu ($R^2 = .29$). This result indicates that less variable RTs for Monitoring/Updating relate to efficient choice RTs that derive from quick basic RT, but conservative decision-making.

Monitoring/Updating Tau. Monitoring/Updating Tau was Gamma distributed and an Adaptive Elastic Net Generalized Regression with Gamma distribution model was utilized.

Model fit was $R^2 = .35$ and one variable, 0-bit Tau, significantly contributed to the model. Drift rate predicted 0-bit Tau ($R^2 = .74$). These results indicate that fewer extremely long RTs for Monitoring/Updating relate to fewer extremely long simple mental speed RTs that derives from quicker information accumulation.

Inhibition Factor

Inhibition Mu. Inhibition Mu was LogNormal distributed and an Adaptive Elastic Net Generalized Regression with LogNormal distribution model was utilized. Model fit was $R^2 = .61$ and two variables, 1-bit Mu and 1-bit Tau, significantly contributed to the model. DM boundary separation and non-decision time predicted 1-bit Mu ($R^2 = .29$), indicating that efficient choice RT derives from faster non-decision RTs and a less conservative (i.e., lower) boundary separation. Also, drift rate predicted 1-bit Tau ($R^2 = .13$), indicating that fewer extremely long choice RTs occur with faster information accumulation. These results indicate that efficient RTs for the Inhibition factor relate to both efficient choice mental speed and fewer extremely long choice mental speed RTs and that better performance on this factor is a function of fast non-decision speed as well as faster information accumulation and lower, less conservative boundaries to respond.

Inhibition Sigma. Like Inhibition Mu, this aspect of the Inhibition factor related to 1-bit Mu, with model fit of $R^2 = .24$. Boundary separation and non-decision time predicted 1-bit Mu ($R^2 = .29$), indicating that less variability in the Inhibition factor relates to faster non-decision RT and a less conservative boundary.

Inhibition Tau. Inhibition Tau was Gamma distributed and an Adaptive Elastic Net Generalized Regression with Gamma distribution model was utilized. Model fit was $R^2 = .21$ and one variable, 0-bit Tau, contributed significantly to the model. Drift rate predicted 0-bit Tau (R^2

= .74). These results indicate that fewer extremely long RTs for the Inhibition factor relate to fewer extremely long simple mental speed RTs that derive from quicker information accumulation.

Diffusion Modeling and Task Complexity

DM parameters for the four ECTs and six executive tasks are presented in Table 8. Two one-way repeated-measures ANOVAs using three ECTs (0-bit excluded) and the six executive tasks, one for boundary separation and another for drift rate. Results of pairwise *t*-tests comparisons between tasks for boundary separation and drift rate are presented in Tables 9 and 10, respectively.

Boundary Separation. Mauchly's Test of Sphericity indicated that the independent variable of boundary separation had violated the assumption of sphericity, $\chi^2(35) = 133.831$, $p < .001$. Utilizing Greenhouse-Geisser correction, there was a main effect of boundary separation, $F(4.430,181.638) = 38.990$, $p < .001$, partial $\eta^2 = .487$. Bonferroni correction was made for 17 comparisons.

Elementary Cognitive Tasks. For the ECTs, statistical significance was found between all three tasks in an ordinal manner. The 2-bit IR task had greater boundary separation than the 1-bit IR task, $t(42) = -6.834$, $p < .001$, and that of the 1-bit IR task was greater than that of the 1-bit non-executive task, $t(42) = -3.507$, $p < .002$.

Executive Function Tasks. No statistically significant differences in boundary separation were found within Shifting and Monitoring/Updating factors, all $p > .002941$. Shifting tasks had greater boundary separation than Monitoring/Updating tasks, all $p < .002$. The NL task boundary separation was significantly greater than all Inhibition and Monitoring/Updating tasks, all $p < .002941$.Within Inhibition, Stroop had greater boundary separation than STOP-IT, $t(41) =$ -

12.006, $p < .001$. STOP-IT had lower boundary separation than any of the other five executive tasks, all $p < .001$. Stroop task boundary separation did not statistically differ from either Monitoring/Updating task or the CS task, all $p > .002941$.

Drift Rate. Mauchly's Test of Sphericity indicated that the independent variable of drift rate had violated the assumption of sphericity, $\chi^2(35) = 124.394$, $p < .001$. Utilizing Greenhouse-Geisser correction, there was a main effect of drift rate, $F(4.815,197.430) = 144.172$, $p < .001$, partial $\eta^2 = .779$. Bonferroni correction was made for 17 comparisons, such that the new significance criterion was $p = .002941$.

Elementary Cognitive Tasks. For the ECTs, statistical significance was found between all three tasks in an ordinal manner. The 1-bit non-executive task had faster drift rate than the 1-bit IR task, $t(42) = 7.387$, $p < .001$, and that of the 1-bit IR task was faster than that of the 2-bit IR task, $t(42) = 8.607$, $p < .001$.

Executive Function Tasks. No statistically significant differences in drift rate were found within Inhibition, Shifting, and Monitoring/Updating factors, all $p > .002941$. The PU task had faster drift rate than all Shifting and Inhibition tasks, all $p < .001$. The SMS task had faster drift rate than either Shifting task and the STOP-IT task, all $p < .001$. The Stroop task had faster drift rate than both Shifting tasks, all $p < .001$.

Relationships between Diffusion Model Parameters. These analyses sparked interest in determining how boundary separation and drift rate were related for each task. Table 11 reports the Pearson correlations for the ECTs and six executive tasks. The ECTs did not have significant correlations between these two parameters. For Inhibition, only the STOP-IT task demonstrated a negative relationship, $r(41) = -.342$, $p < .05$. For Monitoring/Updating, the SMS task had a positively-trending relationship, $r(41) = .296$, $p = .054$. Interestingly, both Shifting tasks had positive correlations: CS task $r(41) = .348$, $p < .05$, NL task $r(41) = .407$, $p < .01$.

Discussion

One of the major arguments for using non-Gaussian statistics for RT data is that it better describes the shape of the distribution. Separating out the Gaussian mean into Gaussian Mu and non-Gaussian Tau is not expected to yield noticeable differences in simple RT or some choice RT tasks. Executive tasks, however, tell a different story: for example, the 2-bit IR ECT Gaussian mean = 1050ms, while the Mu = 609ms and Tau = 436ms. This separation is important to capture because it demonstrates that slower RTs are inherently different from efficient RTs. There is a consistent pattern across all tasks with an executive component (both ECT and EF) that Mu is noticeably lower than the Gaussian mean, which appears inflated as a result. While Gaussian statistics are easy to use and widespread, they are clearly not the best approach for measuring RT, which is one of the most widely used measurements in psychology. Shifting to Non-Gaussian statistics would not be very easy, but it would be scientifically correct to do so in the interest of better describing the ever-present phenomenon of time.

Distribution fit was another major component of the analyses. All but one EF task and the most complex ECT best fit an ex-Gaussian distribution, which is consistent with the literature. However, the 1-bit IR ECT and STOP-IT tasks best fit a Normal-3 distribution. There may be several reasons why this is the case. For example, they may not be sufficiently complex to produce greater RT variability that would be better described as ex-Gaussian. The 1-bit IR task was statistically significantly different on both boundary separation and drift rate from its neighboring ECTs, but the mean difference in boundary separation appeared rather one-sided (.958 vs. 1.171 vs. 1.877). STOP-IT also had the lowest boundary separation of all 10 tasks. This suggests that a task's boundary separation is related not only to the complexity of its demands, but also to the complexity of the RTs it produces, such that a sufficiently complex task can no longer be best captured using only normal distributions (Gaussian or normal-mixtures).

Additionally, even though the task trial-level RT data was mostly ex-Gaussian, the best-fit distribution for each non-Gaussian parameter (Mu, Sigma, Tau) was not consistent. This suggests that relying solely on ex-Gaussian statistics as the *de facto* solution for the inaccuracy of Gaussian RT statistics is too simplistic. Adopting a flexible methodological approach is considerably more difficult, but it is also more scientifically sound to measure and evaluate phenomena in the most accurate and reliable ways available to us.

The EF tasks were designed to be of consistent and limited difficulty, while also providing enough RT variability for DM analyses to distinguish between tasks. EF task accuracy ranged from 89.56-95.21% (excluding STOP-IT), suggesting task development goals were successful. The sample size precluded exploratory factor analysis to identify latent factors, although composite scores for each factor were created. Generalized Regression analyses demonstrated the complex interactions between the EF tasks and a set of Jensen tasks with stepwise complexity progression and demands.

Hypotheses 1 was partially supported. No EF factors were solely predicted by IR ECTs and most had a mixed contribution of non-executive and IR predictors.

Shifting was predicted by 1-bit IR and 0-bit, but was not predicted by 2-bit IR, which offers no support for Hypothesis 2. Shifting is related to ECT performance, but understanding the Shifting factor as measured with RT tasks requires modeling the entire RT distribution and each aspect of the distribution is related to different aspects of ECT performance. The Gaussian component of Shifting is most related to basic internal rule EF mental speed. This indicates that doing well on Shifting tasks requires the ability to overcome automatic response tendencies. Unfortunately, this aspect of ECT performance is not well accounted for by a diffusion model of RT tendencies. In contrast and somewhat unexpectedly, extremely long RTs in Shifting tasks are most related to simple RT speed. Some researchers (Botvinick, Braver, Barch, Carter, & Cohen, 2001; McVay & Kane, 2010; McVay & Kane, 2012; Smallwood & Schooler, 2006) have assumed that the tau variable in an ex-Gaussian distribution is related to executive failure; however, this does not seem to be the case in Shifting tasks. Other literature offers the perspective that tau reflects higher-order processes and is correlated with higher cognitive functions (Matzke & Wagenmakers, 2009; Schmiedek, Oberauer, Wilhelm, Süβ, & Wittmann, 2007). Instead, extremely long RTs in Shifting tasks seems to occur as a result of slow simple RTs that are more variable and have a higher than typical number of extremely long RTs.

Monitoring/Updating was predicted by all ECTs but 1-bit IR, which offers no support for Hypothesis 3. Monitoring/Updating aspects of working memory are related to EF as measured by ECT RTs. This was surprising, as Shifting was expected to have the strongest relationship with 2-bit IR and Inhibition was expected to be most related to all ECTs. The Gaussian component of the ex-Gaussian distribution in Monitoring/Updating is well-predicted by efficient responding in both complex internal rule tasks and a choice RT task. This result suggests that to hold in mind the contents of working memory and regulate those contents, one must be efficient in keeping multiple mental rules in mind and switching between those rules easily. However, one must *also* be fast in choice decision-making. As in Shifting, the exponential component of Monitoring/Updating is again unexpectedly related to simple mental speed and not EF aspects of the ECTs. Specifically, few extremely long RTs in Monitoring/Updating is related to few extremely long RTs in a simple mental speed task without decisional aspects.

Inhibition was solely predicted by non-executive tasks and offers partial support for Hypothesis 4. Inhibition related almost exclusively to choice RT and evidenced no relationship to the internal rule tasks, like the Updating factor in the Santos (2016) study. This result is in direct contrast to what would be expected from Miyake's (2000) EF framework and needs further explication by theoretically-driven experimental work. It is, however, consistent with findings in the developmental literature on the emergence of EF. Studies of young children indicated a unitary factor structure consisting of inhibition (Espy, Martin, Bull, & Stroup, 2006; Wiebe, Espy, & Charak, 2008). Given that young children have very limited frontal lobe development, inhibition is the first executive control ability they develop that can be reliably measured. Maturation and further brain development give rise to more advanced EFs, such that inhibition may become, as seen in our results, a more basic, underlying executive ability. Therefore, the relative time length of time available to practice and develop inhibition is proportionally longer than other EFs, suggesting it becomes less effortful over time, which may explain the non-executive contributions our Inhibition tasks had in the study.

Analysis of DM parameters revealed several insights regarding task structure and complexity. Both boundary separation and drift rate offer different ways to quantify and interpret task difficulty and demands. For boundary separation, Shifting tasks appeared to require the greatest amount of information to reach a decision, followed by the Stroop task, both Monitoring/Updating tasks, and the STOP-IT task. For drift rate, Monitoring/Updating tasks appeared to have the fastest accumulation of information over time, followed by Inhibition tasks, and finally Shifting tasks. These results provide variable but mostly positive support for Hypotheses 5 and 6, as EF relationships with IR ECTs were reflective of greater task complexity.

Lack of statistical differences within factors on both parameters, save for Inhibition, suggests relatively similar complexity between tasks developed for that factor. Inhibition tasks, however, differed on boundary separation, but not drift rate. This suggests that an individual taking the Stroop task requires more information to reach a decision than on the STOP-IT task, yet the information is accumulated at similar speeds across both tasks. Taking both types of parameters into account, Shifting tasks have the greatest overall boundary separation and the slowest overall drift rate, suggesting the demands of Shifting are the most complex. Monitoring/Updating had the second greatest boundary separation and the fastest drift rate, while Inhibition had a variable boundary separation (Stroop>Monitoring/Updating>STOP-IT) and the second fastest drift rate. Because the boundary separation split in Inhibition may be related to specific task demands, Monitoring/Updating may be interpreted as being more complex than Inhibition, while having faster drift rate may be interpreted as being less complex than Inhibition using their relative rankings alone, However, the fact that Inhibition was not predicted by internal rule ECT parameters may suggest lower complexity relative to Monitoring/Updating.

Correlational analyses between boundary separation and drift rate within-task offered a slightly different perspective. Greater task complexity is associated with greater boundary separation (i.e., more information needed to reach a decision) and slower drift rate (i.e., slower information accumulation over time), such that a negative relationship between the two would be assumed. However, the results were remarkably inconsistent with expectations. Both Shifting tasks had significant positive correlations, while only one of two Monitoring/Updating tasks (SMS) had a positively-trending correlation. Because the Shifting tasks both have the greater boundary separation and the slowest drift rate among the tasks, it is surprising to see a positive correlation between the parameters. STOP-IT was the only task to have a significant negative correlation between the parameters, $t(41) = -.342$, $p < .05$.

The DM correlational results suggest that when executive tasks are designed to challenge the participant while simultaneously being relatively easy (89.56% minimum overall accuracy per task), the RT paradigm continues to place a premium on speed. Greater positive correlations here suggest participants require more critical response-dependent information, but are also able to accumulate this information relatively quickly to reach the decision. Inhibition tasks are a curious outlier here, likely because task performance involves stopping automatic responses. In both tasks, the information necessary to make the decision is qualitatively non-complex (i.e., sound cue or word color).

The STOP-IT task is unique in this study in that it was not developed by the author and provides the participant with the option to not provide a response. Most research using stop signal tasks like STOP-IT actually uses the stop-signal RT (SSRT) as the dependent variable. This is a derived estimate of how long it takes to inhibit a response, obtained by subtracting the final stop-signal delay from the no-signal RT (i.e., trials with no inhibition component). Better performance on stop signal tasks involves achieving a larger stop signal delay, rather than a slower no-signal RT, as it is not beneficial to wait for a stop signal that may never be presented on that trial. Additionally, SSRT is a task-level measure, and there is no clear procedure on how to estimate it at the trial level. Responses on all other tasks in this study produced RTs to be evaluated, which cannot be directly compared to an estimate of a non-response. As this study aimed to evaluate task performance using trial-level data, the distribution and diffusion model parameters for STOP-IT in this study took into account both zero and non-zero RTs. So while

SSRT is the primary variable used to measure inhibition in the literature, its derived nature precluded its use in this study.

STOP-IT boundary separation (0.873) is closer to the starting position of the diffusion model (0.5), while Stroop's is markedly higher (1.923). These parameters are unlikely to fully appreciate everything about the task. The captured STOP-IT RTs are predominantly fast or zero. The zero-RT trials, which are labeled as correct, may be artificially making the diffusion model interpret the task as less complex, as there is no way to quantify trial-level inhibition with a non-zero number. This may explain why STOP-IT did not perform as expected compared to other executive tasks that required a response to demonstrate a cognitive process was taking place.

One major aim of this study was to use full RT distributions. Most RT research excludes outliers, typically setting the cutoff at two standard deviations above the mean. This procedure is meant to prevent extreme values from influencing measures of central tendency. Qualitatively, these extreme values may represent inattention, executive failure, fatigue, or a number of different factors. Excluding them necessarily makes the RT distribution more normal by decreasing the amount of RTs contributing to Tau. Some researchers also normalize their data, such as the previous work by Santos (2016), but that procedure is at odds with the aim if this study. For this study, a cutoff of three standard deviations was utilized to retain more RT diversity. Extreme value frequency for the ECTs ranged from 1.28-1.94% and ranged from 1.31-2.15% for the executive tasks, with differences in normal distribution mean ranged from 5-63ms. STOP-IT average non-zero RTs were 7ms different, but were significant at $p = .024$, while all other tasks were significant at $p < .001$. This suggests that even when a small minority of RTs is excluded resulting in a minute difference in absolute average, their contributions to the distribution are nonetheless important in better understanding their underlying process.

Overall, each EF factor related in unexpected ways to the stepwise progression of cognitive demands in the ECTs. Internal rule ECT parameters were primary predictors of Shifting and Monitoring/Updating performance, but non-executive ECT parameters were more contributory overall than expected. Inhibition appeared to be the least complex EF factor, have the least within-factor task consistency, and the most influence on performance from non-executive aspects. Shifting was consistently the most complex EF factor, although its ECT contributions were different than expected.

These results suggest that EF factors are not easily understood, even when using the best available methods. However, these methods are able to give new insights into the structure of EF that traditional Gaussian methodology and interpretation cannot. The EF tasks developed for this study stand in opposition to, but also as a complement to, traditional neuropsychological approaches to EF evaluation. While the results do not look promising for Inhibition, Shifting and Monitoring/Updating tasks were substantiated as having an EF nature. However, the influence of basic non-executive decision-making is difficult to exclude from general problem-solving.

As mentioned at the outset, real-world problem-solving favors quick, efficient solutions due to limited resources and availability of time to enact those solutions. Real-world problems can be of variable difficulty, and we have limited ability to predict the difficulty of a given problem as it presents itself. The tasks used in this study were of different complexities, which is suggestive of difficulty, but overall participant accuracy suggested they were relatively easy. This allowed the differences identified in analyses to stem from RT distributions rather than other potential confounds, as well as avoiding the methodological problems of the "power"/"speed" taxonomy of modern day psychological measurement. Due to the controlled nature of the tasks, it is the participant's problem-solving efficiency that is highlighted. As no similar tasks are used to formally evaluate EF, developing such tasks for wide use is recommended. Using both accuracy and efficiency approaches to EF would allow for a better understanding of EF both on a group and an individual level.

Limitations

The primary limitation of this study is its relatively small sample size. A sample of 150 participants was sought, as similar RT studies typically have between 100 and 200 participants (e.g., Miyake et al., 2000). One reason that recruitment efforts may have been impacted is the estimated study session length. The subject pool posting explained that although the study would take approximately 1.5 hours, they would receive two hours of course credit for their time. Although this represents greater reward for their time, most undergraduate research studies advertised concurrently with the present study lasted only one hour. This decreased time commitment and greater time slot availability likely provided greater flexibility for participants. This smaller sample size also precluded the use of factor analysis for this study, which requires a bare minimum of 100 cases. Evaluating the factor structure of the executive tasks was meant to address several of the initial study hypotheses, although some of them were addressed in a similar way given the available methods.

Given the strong non-executive contributions to the Inhibition tasks, one must consider how construct purity of the tasks used in the study. All tasks were developed by adapting an existing paradigm for use with RT and highlighting the construct as much as possible. Modern psychological EF measures frequently tap multiple domains, but they are distinguished by their unique properties rather than by their commonalities. For example, both the D-KEFS Verbal Fluency Switching subtest and the Wisconsin Card Sorting Test involve a Shifting component, but the latter is considered more challenging and involving “cognitive flexibility.” However, as constructs are theoretical and our methods of development and measurement are imperfect, it may never be possible to develop a task that fully pure to one domain. Additionally, the no-response nature of STOP-IT trials that specifically measure inhibition may not have been interpreted by the diffusion model, which relies on non-zero responses to estimate complexity. Therefore, conclusions regarding its complexity and subsequent relationship to other tasks were limited.

Future Directions

As mentioned above, further development of RT-based EF (and other cognitive domains) would represent an important shift in psychological practice and research. This should ideally be accompanied by better statistical training, as non-Gaussian statistics and diffusion modeling can be difficult to understand. However, they currently represent the best methods for investigating RT, a key variable in psychological research. Multi-site clinical trials are moving towards the use of computerized measures for ease of data collection and collaboration. Using computerized measures would enable the recording of RTs for potentially any task. Current proprietary measures (i.e., Conners' Continuous Performance Test, Test of Variables of Attention) currently generate informative summary score, but do not allow access to raw data. Providing research with trial-level data at the millisecond level may help improve our understanding of attention, EF, and other domains. Future research may seek to replicate these results with a larger control sample, in addition to obtaining concurrent data from traditional EF measures (e.g., D-KEFS, WCST, etc.). Further work would gather such data from known clinical groups, particularly those with identified EF impairment (e.g., traumatic brain injury, frontotemporal dementia, schizophrenia, etc.). This could possibly aid clinicians in differential diagnoses, once consistent group performance is established in the literature.

Conclusion

The present study sought to demonstrate the utility of using non-Gaussian statistics and diffusion modeling to more scientifically measure and interpret RT distributions in EF tasks. Descriptive data demonstrated the stark contrasts between solely using Gaussian distribution parameters versus accounting for extreme RTs in a separate parameter. Results successfully demonstrated that the relationship between ECTs, which increase in complexity according to bits of information, and the EF factors are complex and inconsistent with expectations derived from prior research using both "power" and "speed" tasks. DM analyses determined that Shifting tasks have the greatest complexity, suggesting they also require the most cognitive resources. Monitoring/Updating is somewhat less complex than Shifting, while Inhibition appeared to be the sole factor not to be significantly predicted by internal rule ECT performance and was the most variable overall. While the sample size of this study limited the available analyses, the study demonstrated that using more complex methodology is able to provide rich qualitative information about the nature of EF, as well as offer a participant-friendly efficiency-based approach that may offer new insights when used in conjunction with traditional accuracy-based approaches.

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Table 1

Gaussian and non-Gaussian Statistics for the Elementary Cognitive Tasks (ECTs)

	0-bit	1-bit	1bit IR	2-bit IR
Accuracy	0.9986 (0.004)	0.9793 (0.02)	0.9424 (0.08)	0.9041 (0.13)
Errors	0.16 (0.43)	2.49 (2.28)	6.91 (9.37)	11.51 (15.87)
Average RT	310.77 (47.47)	340.25 (64.36)	437.73 (178.71)	1050.60 (291.61)
Average RTSD	60.37 (21.58)	74.95 (27.41)	206.39 (249.17)	449.73 (210.70)
Mu	261.28 (40.99)	285.01 (59.03)	269.2 (90.03)	609.84 (198.02)
Sigma	21.96 (11.29)	31.03 (10.97)	25.94 (34.69)	108.96 (90.24)
Tau	49.32 (17.31)	54.74 (23.7)	164.25 (111.21)	436.61 (239.7)

Note. Values in parentheses are Standard Deviations. RTSD = Reaction Time Standard Deviation. Mu = Mean of the Gaussian component. Sigma = Standard Deviation of the Gaussian component. Tau = Combined mean/standard deviation of the non-Gaussian component.

Table 2

Gaussian and non-Gaussian Statistics for the Color-Shape (CS) Task

	Overall	Non-switch Trials	Switch Trials
Accuracy	0.8956 (0.13)	0.9050 (0.15)	0.8861 (0.12)
Average RT	1349.89 (319.97)	1241.63 (310.46)	1458.15 (349.08)
Switch Cost	216.52 (164.16)		
Mu	651.19 (231.39)		
Sigma	124.8 (110.38)		
Tau	684.86 (275.69)		

Note. Values in parentheses are Standard Deviations. RTSD = Reaction Time Standard Deviation. Switch Cost = Average Switch trial RT minus average Non-switch trial RT. Mu = Mean of the Gaussian component. Sigma = Standard Deviation of the Gaussian component. Tau = Combined mean/standard deviation of the non-Gaussian component.

Table 3

Gaussian and non-Gaussian Statistics for the Number-Letter (NL) Task

	Overall	Number Block	Letter Block	Switch Block	Switch Trials Only
Accuracy	0.9334 (0.07)	0.968 (0.04)	0.9571 (0.05)	0.9188 (0.11)	0.899 (0.11)
Average RT	1112.17 (186.7)	707.97 (102.12)	757.76 (131.79)	1301.82 (245.89)	1488.21 (291.51)
Switch Cost	755.34 (263.55)				
Mu	684.25 (124.79)				
Sigma	134.06 (65.03)				
Tau	611.75 (205.03)				

Note. Values in parentheses are Standard Deviations. Switch Cost = Average Switch trial only RT minus average trial RT for number and letter trials combined. Mu = Mean of the Gaussian component. Sigma = Standard Deviation of the Gaussian component. Tau = Combined mean/standard deviation of the non-Gaussian component.

Table 4

Gaussian and non-Gaussian Statistics for the Stroop Task

	Word	Color	Color-Word
Accuracy	0.9405 (0.14)	0.9562 (0.1)	0.9282 (0.1)
Average RT	722.42 (108.04)	696.54 (118.15)	865.14 (183.87)
Mu			483.52 (79.39)
Sigma			54.06 (40.86)
Tau			402.19 (137.07)

Note. Values in parentheses are Standard Deviations. Mu = Mean of the Gaussian component. Sigma = Standard Deviation of the Gaussian component. Tau = Combined mean/standard deviation of the non-Gaussian component.

Table 5

Gaussian and non-Gaussian Statistics for the STOP-IT Task

SSD	SSRT	SRRT	NSRT	Mu	Sigma	Tau
277.51 (128.39)	275.64 (49.02)	490.94 (89.37)	553.86 (116.54)	446.00 (79.56)	73.33 (34.73)	97.16 (48.02)

Note: Values in parentheses are Standard Deviations. SSD = Stop-Signal Delay, calculated as the signal delay at which the participant is 50% likely to inhibit their response. SSRT – Stop-Signal RT = Calculated time after the stop-signal it takes for the participant to successfully inhibit a response. SRRT = RT for stop-signal trials, when participants did not successfully inhibit their response. NSRT = No-signal RT, RT for no-signal trials when participants respond normally. Mu = Mean of the Gaussian component. Sigma = Standard Deviation of the Gaussian component. Tau = Combined mean/standard deviation of the non-Gaussian component.

Table 6

Gaussian and non-Gaussian Statistics for the Piek Updating (PU) Task

	Overall	Target	Non-Target
Accuracy	0.9521 (0.07)	0.8843 (0.19)	0.986 (0.02)
Average RT	725.28 (191.72)	747.41 (229.22)	714.21 (187.48)
Mu	423.39 (83.18)		
Sigma	48.77 (24.78)		
Tau	295.8 (138.64)		

Note: Values in parentheses are Standard Deviations. Target = trials where the stimulus matches the current target. Mu = Mean of the Gaussian component. Sigma = Standard Deviation of the Gaussian component. Tau = Combined mean/standard deviation of the non-Gaussian component.

Table 7

Gaussian Statistics for the Sternberg Memory Scanning (SMS) Task

	Overall	Target	Non-Target
Accuracy	0.9307 (0.09)	0.9090 (0.12)	0.9525 (0.09)
Average RT	938.44 (224.23)	963.48 (240.32)	913.4 (223.13)
Mu	583.18 (110.91)		
Sigma	83.47 (31.65)		
Tau	346.85 (152.66)		

Note: Values in parentheses are Standard Deviations. Target = trials where the probe digit was in the trial sequence. Mu = Mean of the Gaussian component. Sigma = Standard Deviation of the Gaussian component. Tau = Combined mean/standard deviation of the non-Gaussian component.

Table 8

Diffusion Model Parameters for the Elementary Cognitive Tasks (ECTs) and the Six Executive Tasks

Task	*a*	*v*	*t0*	*st0*	n
1-bit	0.958 (0.346)	5.704 (1.314)	0.253 (0.052)	0.077 (0.039)	43
1-bit IR	1.171 (0.362)	3.673 (1.422)	0.237 (0.077)	0.093 (0.119)	43
2-bit IR	1.877 (0.7636)	1.723 (0.93)	0.472 (0.178)	0.296 (0.3)	43
CS	2.24 (0.928)	1.174 (0.459)	0.46 (0.206)	0.437 (0.39)	43
NL	2.393 (0.865)	1.349 (0.519)	0.442 (0.164)	0.412 (0.338)	43
Stroop	1.923 (0.415)	1.739 (0.66)	0.325 (0.071)	0.11 (0.148)	42
STOP-IT	0.873 (0.447)	1.536 (0.427)	0.335 (0.077)	0.275 (0.129)	43
PU	1.711 (0.364)	2.327 (1.047)	0.317 (0.075)	0.063 (0.102)	43
SMS	1.789 (0.705)	2.001 (0.778)	0.45 (0.105)	0.21 (0.161)	43

Note: Values in parentheses are Standard Deviations. IR = Internal Rule. CS = Color-Shape task. NL = Number-Letter task. PU = Piek Updating task. SMS = Sternberg Memory Scanning task. a = Boundary separation. v = drift rate. t0 = Non-decision time. st0 = variability in non-decision time.

Table 9

Pairwise *t*-tests of Boundary Separation (*a*) between Executive Tasks and ECTs

Comparison		Mean	SD	SE	*t*	df	*p*
CS	Stroop	.3212095	.9800315	.1512221	2.124	41	.040
	STOP-IT	1.3669814	1.0692742	.1630628	8.383	42	<.001*
NL	Stroop	.4590881	.9078525	.1400847	3.277	41	<.003*
	STOP-IT	1.5184628	.9588388	.1462215	10.385	42	<.001*
PU	Stroop	-.2087738	.4361971	.0673067	-3.102	41	.003
	STOP-IT	.8376163	.4650152	.0709142	11.812	42	<.001*
SMS	Stroop	-.1457119	.8180104	.1262217	-1.154	41	.255
	STOP-IT	.9156465	.7891878	.1203500	7.608	42	<.001*
CS	PU	.5293651	.9916121	.1512194	3.501	42	<.002*
	SMS	.4513349	.7117868	.1085465	4.158	42	<.001*
NL	PU	.6808465	.8238398	.1256344	5.419	42	<.001*
	SMS	.6028163	1.0065692	.1535004	3.927	42	<.001*
CS	NL	-.1514814	1.1621877	.1772320	-.855	42	.398
PU	SMS	-.0780302	.7474929	.1139916	-.685	42	.497
STOP-IT	Stroop	-1.0494452	.5664756	.0874091	-12.006	41	<.001*
1-bit	1-bit IR	-.2126558	.3975713	.0606291	-3.507	42	<.002*
1-bit IR	2-bit IR	-.7063116	.6777626	.1033578	-6.834	42	<.001*

Note: * Significance at the $p < .002941$ level following Bonferroni correction for 17 comparisons. Values in parentheses are Standard Deviations. IR = Internal Rule. CS = Color-Shape task. NL = Number-Letter task. PU = Piek Updating task. SMS = Sternberg Memory Scanning task.

Table 10

Pairwise *t*-tests of Drift Rate (*v*) between Executive Tasks and ECTs

Comparison		Mean	SD	SE	*t*	df	*p*
CS	Stroop	-.5579167	.6814582	.1051513	-5.306	41	<.001*
	STOP-IT	-.3624767	.5586332	.0851908	-4.255	42	<.001*
NL	Stroop	-.4352714	.7283696	.1123899	-3.873	41	<.001*
	STOP-IT	-.2069698	.5958452	.0908655	-2.278	42	.028
PU	Stroop	.5528976	.9866229	.1522392	3.632	41	<.001*
	STOP-IT	.7908000	.9996879	.1524510	5.187	42	<.001*
SMS	Stroop	.2493500	1.0184311	.1571473	1.587	41	.120
	STOP-IT	.4651628	.7330270	.1117856	4.161	42	<.001*
CS	PU	-1.1532767	.8797275	.1341572	-8.596	42	<.001*
	SMS	-.8276395	.6367722	.0971068	-8.523	42	<.001*
NL	PU	-.9977698	.9385661	.1431300	-6.971	42	<.001*
	SMS	-.6721326	.7987282	.1218049	-5.518	42	<.001*
CS	NL	-.1555070	.5407066	.0824570	-1.886	42	.066
PU	SMS	.3256372	1.0161793	.1549659	2.101	42	.042
STOP-IT	Stroop	-.2098595	.7696166	.1187544	-1.767	41	.085
1-bit	1-bit IR	2.0311512	1.8030929	.2749691	7.387	42	<.001*
1-bit IR	2-bit IR	1.9502953	1.4858608	.2265916	8.607	42	<.001*

Note: * Significance at the $p < .002941$ level following Bonferroni correction for 17 comparisons. Values in parentheses are Standard Deviations. IR = Internal Rule. CS = Color-Shape task. NL = Number-Letter task. PU = Piek Updating task. SMS = Sternberg Memory Scanning task.

Table 11

Pearson Correlations between Boundary Separation and Drift Rate for the Elementary Cognitive Tasks (ECTs) and the Six Executive Tasks

Task	*r*	*df*	*p*
1-bit	.155	41	.322
1-bit IR	-.077	41	.623
2-bit IR	.091	41	.564
CS	.348	41	.022*
NL	.407	41	.007**
PU	.039	41	.806
SMS	.296	41	.054
Stroop	-.173	40	.274
STOP-IT	-.342	41	.025*

Note: * $p < .05$, ** $p < .01$. Values in parentheses are Standard Deviations. IR = Internal Rule. CS = Color-Shape task. NL = Number-Letter task. PU = Piek Updating task. SMS = Sternberg Memory Scanning task. a = Boundary separation. v = drift rate.

Appendix A: Demographic and Academic Information Form

Demographic Information:

ID #: ________ **Age**: ______ **Sex**: M/ F **Handedness**: Right / Left / Ambidextrous

Highest Level of Education or Year in School: ____________________

Primary Language: ____________________ (If fluent in several, note all)

How many people are in your immediate family (includes only self, biological parents, siblings w/ same parents as you)?: ____ **How many are left-handed?** _____

What race or ethnicity do you associate most strongly with (circle all that apply)?

African American Caucasian Hispanic Asian and Pacific Islander

Native American Middle Eastern Other:________________________

History of Psychological Conditions:

Do you or anyone in your immediate family have any of the following? If YES, what and in whom? When diagnosed and by whom (family doctor, psychologist, etc.)?

Psychiatric disorders (e.g., depression, anxiety, schizophrenia)? Y / N ______________

____

Learning disabilities (e.g., dyslexia, reading disorder, math disorder)? Y / N _________

____

ADHD? Y / N ____

____

Neurological disorders (e.g., epilepsy, dementia, Alzheimer's, Parkinson's)? Y / N ____

____

Self only: **Head trauma** (e.g., concussion, traumatic brain injury, stroke)? Y / N _______

____

If YES: Lost consciousness? Y / N How long? ________ Overnight hospital stay? Y / N
: Received treatment? Y / N what kind? ___________ Permanent damage? Y / N
If CONCUSSION: how long did symptoms last? ________ Any more since then? Y / N

Are you currently taking any prescription medication? Y / N
If YES: name, dosage, frequency, how long have you taken it?: ____________________

____

____

Do you have any vision-related problems (not including glasses/contacts)? Y / N____

____

Academics (from transcript):

Major Field of Study ______________________ Overall GPA _____________
Average credits completed/semester ________________ [calculate]
Withdrawals/Drops (W/WR)________ Incompletes (I) ________ D+ or lower________

Dmitriy Kazakov, M.S, M.A.

University Address:
2441 E. Hartford Ave. Garland Hall 338D
Milwaukee, WI 53211
(414) 229-4746
dkazakov@gmail.com

EDUCATION

2012-2019 Ph.D. **Clinical Psychology**, **University of Wisconsin–Milwaukee** (APA-accredited)
Dissertation: *Evaluation of Cognitive Control using Non-Gaussian Reaction Time Distributions in Fractionated Executive Function Tasks*

2012-2016 M.S. **Psychology**, **University of Wisconsin–Milwaukee** (APA-accredited)
Thesis: *Eye Movement Effects in Simulated Object Recognition Memory Impairment*

2009-2011 M.A. **Forensic Psychology**, **John Jay College of Criminal Justice**

2006-2009 B.A. **Psychology** (Cum Laude), **University of Nevada–Las Vegas**

CLINICAL INTERNSHIP (APA-ACCREDITED)

2018-2019 **Minneapolis VA Health Care System** – Clinical Psychology, Neuropsychology Track
Supervisors: Greg Lamberty, Ph.D., ABPP, Anita Sim, Ph.D., ABPP, Torricia Yamada, Ph.D., Carolyn Anderson, Ph.D., ABPP, Christie Clason, Ph.D., Sheena Czipri, Psy.D., Wendy VanVoorst, Ph.D, ABPP

- Rotations: General Neuropsychology, Rehabilitation Neuropsychology
- Adjunctives: Cognitive-Behavioral Social Skills Training (CBSST), Motivational Interviewing (MI), Assessment Clinic, Research
- Assisted with pre/post-treatment neuropsychological evaluations for the Chronic Pain Rehabilitation Program (CPRP), participated in brain cuttings, fact-finding, and seminars.

CLINICAL EXPERIENCE

2017-2018 **ProHealth Waukesha Memorial Hospital**, Adult Neuropsychology Service
Supervisors: Eben Schwartz, Ph.D., Julie Janecek, Ph.D., ABPP, Pamela McMurray, Ph.D., ABPP, Gina Rehkemper, Ph.D., ABPP

- Obtained advanced practicum-level training in selecting test batteries, administering and scoring neuropsychological assessments, interviewing, report writing, and attending case conferences and ethics board meetings.

2016-2017 **Froedtert & Medical College of Wisconsin**, Adult Neuropsychology Service
Supervisors: Sara Swanson, Ph.D., ABPP, Julie Bobholz, Ph.D., ABPP, Michael McCrea, Ph.D., ABPP, David Sabsevitz, Ph.D., ABPP, Laura Umfleet, Psy.D.

- Obtained practicum-level training in administering and scoring neuropsychological assessments, writing integrated reports, assisting with interviews, and attending didactics (e.g., journal club, case conferences, seminars, grand rounds).

2015-2016 **Sacred Heart Rehabilitation Institute**, Brain Injury Day Treatment Program
Supervisor: David Osmon, Ph.D., ABPP

- Obtained practicum-level training in interviewing, co-facilitating rehabilitation groups, consulting with and assisting allied health professionals during individual sessions, and developing and implementing individualized neurorehabilitation protocols using empirically-supported techniques.

2013-2015 **University of Wisconsin-Milwaukee**, Learning Disability Specialty Clinic
Supervisor: David Osmon, Ph.D, ABPP

- Administered comprehensive neuropsychological and psychoeducational assessments on a weekly basis for university ADHD/LD referrals, supervised assessments of first-year doctoral students.

2014-2016 **University of Wisconsin-Milwaukee**, Psychology Department Clinic
Supervisors: Christopher Martell, Ph.D., ABPP, Robyn Ridley, Ph.D.

- Learned and provided Cognitive-Behavioral Therapy (CBT) and behavioral activation (BA) interventions to university and community therapy clients presenting with depression, general anxiety, and adjustment disorders.

2012-2014 **University of Wisconsin-Milwaukee**, Psychology Department Clinic
Supervisors: Bonita Klein-Tasman, Ph.D., Han Joo Lee, Ph.D

- Conducted clinical interviews, administered comprehensive psychoeducational and neuropsychological evaluations, and wrote integrated reports.

2012-2015 **University of Wisconsin-Milwaukee**, Psychology Department Clinic
Supervisors: Christopher Martell, Ph.D., ABPP, Jonathan Kanter, Ph.D., Shawn Cahill, Ph.D., Robyn Ridley, Ph.D.

- Participated in weekly group supervision/consultation meetings regarding therapy cases, investigated relevant research and therapy literature to address practice questions for therapists, observed live and recorded therapy sessions.

2011-2012 **Coney Island Hospital Dept of Behavioral Health**, Chemical Dependency Services
Supervisor: Lisa Baron, Ph.D.

- Obtained practicum-level training in co-facilitating therapeutic and psychoeducational groups for MICA outpatients, conducting biopsychosocial and intake assessments, providing statistical and research support for program improvement initiatives.

EMPLOYMENT

2009-2010 **Block Institute, Inc. Article–16 Clinic**, Treatment Coordinator
Supervisors: Balaji Oruganti, Ph.D, Jordana Kenny, LCSW

- Provided case management and treatment coordination services for developmentally disabled adults and caregivers, presented at case conferences in the clinic and residential settings, and managed a database of confidential medical information.

RESEARCH EXPERIENCE

2012-2019 **UWM Adult Neuropsychology Research Laboratory**, Graduate Researcher
Supervisor: David Osmon, Ph.D., ABPP

- Developed research projects utilizing neuropsychological assessments and eyetracking to investigate memory and malingering, effort testing, and personality; performed literature reviews and statistical analyses; wrote IRB proposals and revisions for research projects; developed grant proposals; contributed scholarly writing to manuscripts; supervised and mentored multiple undergraduate and junior graduate students.

2010-2011 **Investigative Psychology Research Unit at John Jay College**, Student Researcher
Supervisor: C. Gabrielle Salfati, M.Sc., Ph.D., C.Psychol, F.IA-IP

- Developed and completed research investigating thematic classification of crime scene behaviors in serial sexual assaults using the Homicide Profiling Index-Revised (HPI-R).

2010 **FBI Behavioral Science Unit – John Jay College Joint Research**, Student Researcher *Supervisor:* Louis Schlesinger, Ph.D.

- Developed and completed research investigating the progression and escalation of sexual activity, physical violence, and criminal sophistication levels in serial sexual assaults.

2010-2011 **John Jay College Deception Detection Laboratory**, Research Assistant
Supervisor: Maria Hartwig, Ph.D.

- Performed mock interrogation interviews, transcribed and coded study videos for verbal cues, and performed inter-rater reliability analyses for research investigating optimal evidence presentation.

2009-2010 **John Jay College Psychopathy Laboratory**, Research Assistant
Supervisor: Diana Falkenbach, Ph.D.

- Developed a research proposal to investigate the Dark Triad of personality and Five Factor Model traits using a novel measure of Machiavellianism, and trained to use the Psychopathy Checklist-Revised (PCL-R).

2008-2009 **UNLV Patient-Focused Research Laboratory**, Research Assistant
Supervisor: Jeffrey Kern, Ph.D.

- Performed scoring, data entry, and analysis of data collected for a study investigating the efficacy of feedback on therapist ratings of client improvement.

2008-2009 **UNLV Neuropsychology Research Program**, Research Assistant
Supervisor: Daniel Allen, Ph.D.

- Performed administration, scoring, and data entry of neuropsychological, cognitive, emotion, and symptom-report assessments in bipolar disorder and aging populations, performed literature reviews and statistical analyses, and contributed writing to scholarly papers.

2008 **UNLV Auditory Cognitive Neuroscience Laboratory**, Research Assistant
Supervisor: Joel Snyder, Ph.D.

- Operated and maintained an electroencephalograph (EEG) system, collected data for human auditory and visual experiments examining streaming and context effects, and performed literature reviews.

2007-2009 **UNLV Reasoning and Memory Laboratory**, Research Assistant
Supervisor: David Copeland, Ph.D.

- Performed data collection, data entry, test scoring, and stimulus editing; performed literature reviews and statistical analyses; and performed lab management for math cognition and working memory experiments.

PUBLICATIONS

Peer-reviewed Journal Articles:

1. Osmon, D. C., **Kazakov, D.**, Santos, O., & Kassel, M. (2018). Non-Gaussian distributional analyses of reaction times (RT): Improvements that increase efficacy of RT tasks for fractionating cognitive processes. *Neuropsychology Review, 28*(3), 359-376.

2. Osmon, D. C., Santos, O. A., **Kazakov, D.**, Kassel, M. T., Mano, Q. R., & Morth, A. (2018). Big Five personality relationships with general intelligence and specific Cattell-Horn-Carroll factors of intelligence. *Personality and Individual Differences, 131*, 51-56.

3. Santos, O. A., **Kazakov, D.**, Reamer, M. K., Park, S., & Osmon, D. C. (2014). Effort in college undergraduates is sufficient on the Word Memory Test. *Archives of Clinical Neuropsychology, 29*(7), 609-613.

4. Sorochinski, M., Hartwig, M., Osborne, J., Wilkins, E., Marsh, J. J., **Kazakov, D.**, & Granhag, P. A. (2014). Interviewing to detect deception: When to disclose the evidence? *Journal of Police and Criminal Psychology, 29*(2), 87-94.

5. Allen, D. N., Haderlie, M., **Kazakov, D.**, & Mayfield, J. (2009). Construct and criterion validity of the Comprehensive Trail Making Test in children and adolescents with traumatic brain injury. *Child Neuropsychology, 15*(6), 543-553.

In preparation:

1. **Kazakov, D.**, Osmon, D. C., Kapur, N., & Hannula, D. E. Eye movement effects in simulated object recognition memory impairment.

2. Osmon, D. C., Kassel, M. T., Zolliecoffer, C., & **Kazakov, D.** Constructs of mental speed and executive control are differentially associated with crystallized and fluid intelligence.

3. Osmon, D. C., Reamer, M. K., Santos, O. A., **Kazakov, D.**, & Kassel, M. T. Relationship of the Student Adaptation to College Questionnaire to the Big Five factors, cognition, and other college adjustment tasks in learning problem referrals.

PUBLISHED ABSTRACTS OF PRESENTATIONS AT PROFESSIONAL MEETINGS

1. Gracian, E. I., **Kazakov, D.**, Wright, D. O., Austiff, M. B., Osmon, D. C., & Mosack, K. E. (2019, February). Non-uniform age-related differences, concurrent validity, and neuropsychological

correlates of WebEXEC in cognitive normal older adults. Poster presented at the International Neuropsychological Society 47th Annual Conference, New York, New York.

2. Zolliecoffer, C., Kassel, M., **Kazakov, D.**, & Osmon, D. (2018, October). Negative priming Stroop effect: Executive control added to Stroop interference effect. Poster presented at the National Academy of Neuropsychology 38th Annual Conference, New Orleans, Louisiana. *Archives of Clinical Neuropsychology, 33*(6), 703-794.

3. Kassel, M., Zolliecoffer, C., **Kazakov, D.**, & Osmon, D. (2018, October). Differential contributions of executive control to predict intelligence. Poster presented at the National Academy of Neuropsychology 38th Annual Conference, New Orleans, Louisiana. *Archives of Clinical Neuropsychology, 33*(6), 703-794.

4. Gracian, E. I., **Kazakov, D.**, Resch, Z. J., Austiff, M. B., Yang, B., Osmon, D. C., & Mosack, K. E. (2018, February). Non-uniform age-related differences and neuropsychological correlates of medication management ability in cognitively normal adults. Poster presented at the International Neuropsychological Society 46th Annual Conference, Washington, D.C. *Journal of the International Neuropsychological Society, 24*(s1), a-325.

5. **Kazakov, D.**, Loman, M. M., Swanson, S. J., Sabsevitz, D. S., Cohen, S. B., Earing, M. G., & Umfleet, L. G. (2017, October). Executive and adaptive functioning in adults with congenital heart disease. Poster presented at the National Academy of Neuropsychology 37th Annual Conference, Boston, Massachusetts. *Archives of Clinical Neuropsychology, 32*(6), 667-765.

6. **Kazakov, D.**, Osmon, D. C., Kapur, N., & Hannula, D. E. (2014, November). Tell the truth: Eye movements index object recognition despite efforts to simulate memory impairment. Poster presented at the National Academy of Neuropsychology 34th Annual Conference, Fajardo, Puerto Rico. *Archives of Clinical Neuropsychology, 29*(6), 524.

7. **Kazakov, D.**, Duke, L. A., Field, R. B., Allen, D. N., & Mayfield, J. (2009, November). Verbal comprehension and perceptual reasoning deficits predict learning and memory impairment in children with TBI. Poster presented at the National Academy of Neuropsychology 29th Annual Convention, New Orleans, Louisiana. *Archives of Clinical Neuropsychology, 24*(5), 474-475.

8. **Kazakov, D.**, Haderlie, M. M., Terranova, J., Martinez, A. E., Allen, D. N., & Mayfield, J. (2009, November). Factor structure of the Comprehensive Trail Making Test in pediatric traumatic brain injury. Poster presented at the National Academy of Neuropsychology 29th Annual Convention, New Orleans, Louisiana. *Archives of Clinical Neuropsychology, 24*(5), 479.

9. Barney, S. J., Ringdahl, E. N., **Kazakov, D.**, & Allen, D. N. (2008, October). Neurocognitive deficits in bipolar disorder with co-occurring borderline symptomatology. Poster presented at the National Academy of Neuropsychology 28th Annual Conference, New York, New York. *Archives of Clinical Neuropsychology, 23*(6), 706.

10. Bello, D. T., Randall, C., Armstrong, C. M., Barney, S., **Kazakov, D.**, & Allen, D. N. (2008, October). Neurocognitive deficits predict functional outcome as measured by the UCSD Performance-based Skills Assessment (UPSA) in individuals with bipolar disorder. Poster presented at the National Academy of Neuropsychology 28th Annual Conference, New York, New York. *Archives of Clinical Neuropsychology, 23*(6), 651-652.

11. Randall, C., Bello, D. T., Armstrong, C. M., Frantom, L., Ringdahl, E., **Kazakov, D.**, & Allen, D. N. (2008, October). Working memory deficits in psychotic bipolar disorder: Endophenotypes for psychosis. Poster presented at the National Academy of Neuropsychology 28th Annual Conference, New York, New York. *Archives of Clinical Neuropsychology, 23*(6), 653-654.

PRESENTATIONS AT PROFESSIONAL MEETINGS

1. **Kazakov, D.**, Osmon, D. C., Kapur, N., & Hannula, D. E. (2014, April). Eye movements index memory despite simulated recognition impairment. Poster presented at the Wisconsin Psychological Association 2014 Convention, Madison, Wisconsin.

2. Kennedy-Hettwer, E., **Kazakov, D.**, Osmon, D. C., Kapur, N., & Hannula, D. E. (2014, April). Eye movements unmask simulated recognition memory impairment. Poster presented at the 13th Annual UW-System Symposium for Undergraduate Research and Creative Activity, Milwaukee, Wisconsin.

3. **Kazakov, D.**, Ramirez, M., & Schery, C. (2011, May). Thematic classification of crime scene behaviors in serial rape. Presentation given to members of the FBI Behavioral Science Unit at John Jay College of Criminal Justice, New York, New York.

4. Sorochinski, M., Hartwig, M., Osborne, J., Wilkins, E., Marsh, J. J., **Kazakov, D.**, & Granhag, P. A.
(2011, March). Suspect interviewing strategies: When to disclose the evidence? Paper presented at the American Psychology-Law Society 2011 Conference/4th International Congress on Psychology and Law, Miami, Florida.

5. **Kazakov, D.** (2010, December). Physical and sexual violence patterns in serial rape. Presentation given to members of the FBI Behavioral Science Unit at John Jay College of Criminal Justice, New York, New York.

6. Terranova, J., **Kazakov, D.**, McMurray, J., Mayfield, J., Allen, D. N. (2010, October). Construct validity of the WISC-IV in pediatric traumatic brain injury. Poster presented at the National Academy of Neuropsychology 30th Annual Conference, Vancouver, British Columbia, Canada.

7. **Kazakov, D.**, & Falkenbach, D. (2010, May). Reassessing the Dark Triad of personality using a new measure of Machiavellianism. Poster presented at the Forensic Psychology Master's Student Research Group 6th Annual Research Conference, New York, New York.

8. **Kazakov, D.**, Haderlie, M., Barney, S. J., Mayfield, J., & Allen, D. N. (2009, August). Construct validity of the CTMT in traumatic brain injured adolescents. Poster presented at the American Psychological Association 117th Annual Convention, Toronto, Canada.

9. Houska, J. A., Copeland, D. E., Bies-Hernandez, N. J., & **Kazakov, D.** (2009, May). Be bold?: The effects of colored font on recall of syllabus information. Poster presented at the Association for Psychological Science 21st Annual Convention, San Francisco, California.

10. Haderlie, M., Montano, S., **Kazakov, D.**, Sanders, L., Nothman, P., & Kern, J. (2009, April). Patientfocused research: Examining the psychotherapist as a feedback receiver. Poster presented at the Western Psychological Association 89th Annual Convention, Portland, Oregon.

11. Haderlie, M., Thaler, N., **Kazakov, D.**, Sutton, G., Mayfield, J., & Allen, D. (2009, April). The Comprehensive Trail Making Test's sensitivity to traumatic brain injury. Poster presented at the Western Psychological Association 89th Annual Convention, Portland, Oregon.

12. **Kazakov, D.**, Haderlie, M., Barney, S. J., Mayfield, J., & Allen, D. N. (2009, April). Adolescent IQ and executive function associations in traumatic brain injury. Poster presented at the Western Psychological Association 89th Annual Convention, Portland, Oregon.

13. Stolberg, P. C., Sutton, G., **Kazakov, D.**, Mayfield, J., & Allen, D. N. (2009, April). The utility of the Reynolds Intellectual Assessment Scales (RIAS) in the identification of traumatic brain injury. Poster presented at the Western Psychological Association 89th Annual Convention, Portland, Oregon.

14. **Kazakov, D.**, Haderlie, M., Barney, S. J., Mayfield, J., & Allen, D. N. (2008, November). Adolescent IQ and executive function associations in traumatic brain injury. Poster presented at the Psi Chi 1st Annual Psychology Undergraduate Research Conference, Las Vegas, Nevada.

TEACHING EXPERIENCE

01/13 – 05/13 Teaching Assistant	UWM Physiological Psychology
09/12 – 12/12 Grader	UWM Intro Psychology, Psychopathology, Health Psychology
08/08 – 12/08 Teaching Assistant	UNLV General Psychology (Honors)

HONORS, AWARDS, AND SERVICE ACTIVITIES

2016	Psychology Department Summer Graduate Research Fellowship (UWM), University of Wisconsin–Milwaukee
2015-18	Advanced Opportunity Program (AOP) Fellowship, University of Wisconsin–Milwaukee
2014	Ted Blau Memorial Award for Best Student Poster Presentation, National Academy of Neuropsychology
2014	First Place Graduate Poster Award, Wisconsin Psychological Association
2010	Third Place Poster Award, Forensic Psychology Master's Student Research Group Conference, John Jay College
2009-11	Graduate Dean's List, John Jay College
2008	Second Place Poster Award, Psi Chi/Psychology Department Undergraduate Research Conference, University of Nevada–Las Vegas
2008	Access Grant, University of Nevada–Las Vegas
2008	Gilpin Kendall Academic Scholarship, University of Nevada–Las Vegas
2007-09	Dean's Honor List, University of Nevada–Las Vegas

SERVICE ACTIVITIES

2017-18	Treasurer, Association for Graduate Students in Neuropsychology, University of Wisconsin–Milwaukee

2015-17	Student Member, Program Committee, National Academy of Neuropsychology
2015-17	Student Volunteer Coordinator, National Academy of Neuropsychology
2015	Student Member, Honors & Awards Committee, National Academy of Neuropsychology
2014-17	Secretary, Association for Graduate Students in Neuropsychology, University of Wisconsin–Milwaukee
2008-09	Vice President, Psychology Club, University of Nevada–Las Vegas

MEMBERSHIP IN PROFESSIONAL ORGANIZATIONS

National Academy of Neuropsychology

International Neuropsychological Society

American Academy of Clinical Neuropsychology

Society for Clinical Neuropsychology

American Psychological Association

Wisconsin Psychological Association

Western Psychological Association

Psi Chi

SKILLS AND CERTIFICATIONS

Skills: SPSS, Microsoft Office, CPRS, QuadraMed, Epic, DirectRT, Neurobehavioral Systems Presentation

Certifications: Collaborative Institutional Training Initiative (CITI) Social/Behavioral Research, U.S. Department of Justice Federal Bureau of Investigation Research in Violent Behavior Certificate