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Reward-Seeking Deficits in Major Depression:
Unpacking Appetitive Task Performance with Ex-Gaussian Response Time Variability Analysis

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Data Availability Statement

Research materials, data files, and R code are available at Open Science Framework: <https://osf.io/jxqyn/>.

Abstract

Major depressive disorder (MDD) has extensive ties to motivation, including impaired response time (RT) performance. Average RT, however, conflates response speed and variability, so RT differences can be complex. Because recent studies have shown inconsistent effects of MDD on RT variability, the present research sought to unpack RT performance with several key improvements: (1) a sample of adults ($n = 78$; 18 MDD, 60 Control) free of antidepressant medication; (2) an unambiguously appetitive task with appealing incentives at stake; and (3) ex-Gaussian RT modeling, which can unconfound speed and variability by estimating parameters for the mean (μ) and standard deviation (σ) of the normal component and the mean of the exponential component (τ). The groups had comparable μ and σ parameters, but the MDD group had a significantly larger τ , reflecting greater intraindividual RT variability. The findings suggest that MDD's effect on average RT can stem from greater intraindividual variability, not from overall slowness. Possible mechanisms, such as impaired executive processes in MDD and difficulties maintaining stable mental representations of incentives, are considered.

Keywords: motivation; depression; response times; intraindividual variability; ex-Gaussian models

Major depressive disorder (MDD) has extensive ties to motivational processes (Brinkmann & Franzen, 2015; Strauman & Eddington, 2017). The intersections between depression and motivation have been examined for many kinds of outcomes, including neuroimaging during reward-seeking tasks, autonomic markers of effort, and behavioral performance (e.g., Admon & Pizzagalli, 2015; Franzen, Brinkmann, Gendolla, & Sentissi, 2019; Treadway, Bossaller, Shelton, & Zald, 2012). The broad category of behavioral performance includes an array of specific outcomes, such as quantifying the decisions people make, the frequency and patterning of mistakes, and—perhaps the most common outcome—response times (RT).

A broad theme in the literature on MDD and RT performance is that MDD impairs performance on cognitive tasks: people with MDD tend to be slower, reflected in larger mean RT, consistent with the broader “slowing” that can accompany MDD (Caligiuri & Ellwanger, 2000; Den Hartog et al., 2003; Kertzman et al., 2010). Mean RTs, however, are affected not only by factors promoting *speed* but also factors promoting *variability* (Heathcote, Popiel, & Mewhort, 1991; Matzke & Wagenmakers, 2009), so the effects of MDD on RT are more complex than they appear. Because RT distributions are positively skewed and heavy tailed, their means can become correlated with their standard deviations (Nesselroade & Salthouse, 2004). As a result, the mean of an RT distribution can increase because of true slowness or because of greater response variability.

Figure 1 illustrates the issue in a hypothetical two-condition design. In the first panel, the two conditions differ only in their central tendency (the modal region of highest density): one is on average slower than the other. In the second panel, the two conditions have the same central tendency but differ in their variability—one group has a heavier RT tail. In both cases, however, the two groups will differ in their mean RT: in the first panel the RT difference reflects true differences in central tendency, but in the second it reflects differences in RT variability, the intraindividual dispersion in RTs that creates heavier tails. To determine if a condition like

MDD affects response speed, then, RT speed and RT variability must be separated as distinct distribution parameters.

One solution is to model RT distributions and estimate their underlying components, such as an ex-Gaussian model (Matzke & Wagenmakers, 2009). The ex-Gaussian distribution is a convolution of a Gaussian (normal) function and an exponential function. It yields estimates for three parameters: (1) *Mu*, the mean of the normal (Gaussian) component and the central tendency of the RT distribution; (2) *Sigma*, the standard deviation of the normal component; and (3) *Tau*, the mean of the exponential component. *Tau* reflects the distributional skewness responsible for the “heavy tail” of the RT distribution and thus captures intraindividual RT variability. These parameters are illustrated in Figure 1. The distributions in the first panel differ only in *Mu*; the distributions in the second differ only in *Tau*.

To date, results from the handful of studies on MDD and RT variability have been mixed. Nearly all used older metrics of RT variability based on descriptive statistics, such as the individual standard deviation (ISD; the *SD* computed for each participant’s RTs) and the coefficient of variation (CoV; the ISD divided by the individual mean RT; Nesselroade & Salthouse, 2004). One study found that participants with MDD had higher ISD (van den Bosch et al., 1996) and CoV (Kaiser et al., 2008) values than healthy controls; conversely, another study found the opposite CoV effect (Chase et al., 2010). Although easily calculated, ISD and CoV are flawed metrics of RT variability (Stawski et al., 2019). ISD is affected by mean RT levels, so both it and CoV, as the ratio of ISD to mean RT, are impure measures of variation (Hultsch, Strauss, Hunter, & MacDonald, 2008). Only one study has examined MDD using model-based methods. In a rapid sustained attention task, the MDD condition had a higher ISD, but no effects were found for the *Mu*, *Sigma*, or *Tau* parameters from an ex-Gaussian model (Gallagher et al., 2015).

We see two reasons why potential effects of MDD on RT variability may have been obscured. First, past studies were often confounded by medication effects. In all studies but one

(Gallagher et al., 2015), all or nearly all the depressed participants were currently taking antidepressant medications. The effects of antidepressant medications on biobehavioral systems involved in motivation are complex (Der-Avakian & Markou, 2012; Kemp et al., 2010), but antidepressant medications tend to obscure effects of MDD. Second, the tasks used in past work rarely had a reward at stake: performance was not typically tied to an incentive people were striving to attain. Having an explicit, appealing task reward is obviously essential for studying reward-seeking behavior.

In the present research, we unpacked the effects of MDD on RT performance using data from a recent study of depression and effort (Silvia et al., in press). Our sample consisted of adults who, based on clinical interviews, did or did not meet clinical criteria for MDD. All participants were free from antidepressant medications, thus avoiding the complex effects of medication status, and the performance task was explicitly appetitive. Participants received a small cash incentive for each correct response, so rewards were clearly tied to performance. The task RTs were analyzed using ex-Gaussian models as well as older metrics (ISD, CoV) for the sake of comparability with past work. Taken together, the sample, task design, and modeling approach allow us to decompose the effects of MDD on response speed and variability.

Method

Participants

Seventy-eight adults (18 MDD, 60 Control) participated as part of a larger study of depression and motivation (Silvia et al., in press). Two people were omitted from these analyses—one person (MDD) misunderstood the parity task, and another (Control) had no RT data due to equipment error—yielding a sample of 76 people (17 MDD, 59 Control). Based on self-reports, the sample was predominantly female (58 women, 18 men) and diverse (47% African American, 4% American Indian, 7% Asian, 36% European American, 14.5% Hispanic or Latino/a; people could select several or decline to select any). A range of recruitment methods were used to attract people who were experiencing depression as well as people who were not

experiencing mental health issues. Based on power analyses reviewed by the funding agency, the proposed sample size was 70 people; data collection stopped when the project's funding ceased. See the Online Supplemental Material (OSM) for details about the sample, recruitment, and screening.

Procedure

The research was approved by the applicable Institutional Review Board (#14-0143), and all participants provided informed consent. MDD status was evaluated via structured clinical interviews conducted by trained graduate students in clinical psychology using select modules of the Structured Clinical Interview for DSM disorders (SCID-5-RV: First, Williams, Karg, & Spitzer, 2015; SCID-II: First, Gibbon, Spitzer, Williams, & Benjamin, 1997). To avoid effects of medication, all participants were ineligible if they had taken antidepressants within the past 8 weeks. Additional ineligibility criteria included presence of active suicidal ideation, antisocial or borderline personality disorder, current symptoms of substance abuse or dependence, any clinically significant psychotic symptoms, or history of manic or hypomanic episodes.

Parity task. Data collection involved individual sessions conducted by a same-gender experimenter. The appetitive task was a digit parity task (Framorando & Gendolla, 2018; Harper, Eddington, & Silvia, 2016; Silvia, Sizemore, Tipping, Perry, & King, 2018). This task presents a word flanked by 2 numbers (e.g., 8 BENCH 5). People must ignore the word and indicate if the numbers have the same parity (i.e., the digits are both odd or both even) or different parity (i.e., one is odd, one is even) by pressing one of two buttons on a high-speed keyboard with a timing accuracy of 1 ms. The item remained on-screen until a response was made, which triggered another trial.

Task incentive. The instructions emphasized that the goal was to make as many correct responses as possible. As an incentive, people received a small amount of money, to be paid in cash at the end of the session, for each correct response. All correct responses were rewarded, and mistakes were not penalized. Because the task was self-paced, a faster rate of

correct responses would gain more rewards. The task's appetitive structure is thus intuitive and straightforward. People completed two blocks—3 minutes per block, with a 90-second break—each with a different incentive level manipulated within-person (Harper et al., 2018). Based on the block, correct responses earned 3 cents (3c) or 15 cents (15c) each.¹

Results and Discussion

Data Preparation

Preparing the RTs for analysis involved (1) omitting incorrect responses (3c: 7.16%; 15c: 6.48%) and (2) omitting RTs smaller than 200 ms (0% omitted) and greater than 5000 ms (3c: .45%; 15c .52%). The data were processed in R 4.0 (R Core Team, 2020) using ex-Gaussian functions from *retimes* (Massidda, 2015) and then analyzed in Mplus 8 using maximum likelihood with robust standard errors. Because the predictor (MDD vs Control) is categorical, the regression coefficients are *Y*-standardized: they represent the difference in the outcome, in its *SD* units, between the MDD and Control conditions (Long, 1997) and can thus be interpreted in the convenient Cohen's *d* effect-size metric for group differences. Preliminary analyses found no differences between the 3-cent and 15-cent incentives (see OSM for details and plots), so the two blocks were averaged. Table 1 displays the descriptive statistics.

Effects on Response Time Variability

We first examined the effects of MDD on metrics based on the observed RT distribution: the mean RT, ISD, and CoV (see Figure 2). Regression models found a marginal effect on mean RT ($b = .45$, $SE = .26$, $p = .078$), reflecting a trend for slower response times in the MDD condition. Significant effects appeared for both ISD ($b = .58$, $SE = .25$, $p = .018$) and CoV ($b = .68$, $SE = .22$, $p = .002$), reflecting larger intraindividual variability in RT in the MDD condition.

Next, we examined parameter estimates of the RT distribution from the ex-Gaussian

¹ The experiment had two between-person counterbalancing factors. First, half the participants completed the 3-cent block first; the other half completed the 15-cent block first. Second, two sets of parity stimuli (nouns and digits), varied orthogonally to incentive value, were created to avoid familiarity effects. Preliminary analyses found no main effects or interactions involving incentive order or stimuli set, so they are not discussed further.

decomposition. Figure 3 displays the estimated distributions for the Control (white) and MDD (grey) conditions. Visually, the two conditions appear to have the same central tendency (μ), but the MDD condition appears much more variable. Indeed, regression models predicting the ex-Gaussian parameters (see Figure 4) found no difference for the μ ($b = -.03$, $SE = .26$, $p = .915$) and σ ($b = .13$, $SE = .33$, $p = .686$) parameters. The MDD group, however, had a significantly larger τ ($b = .65$, $SE = .24$, $p = .007$), reflecting greater RT variability.

Discussion

The findings illustrate the complicated nature of mean RT and descriptive variability metrics such as ISD and CoV (Hultsch et al., 2008). For these observed metrics, the MDD group had a marginal trend toward being slower and a significantly higher ISD and CoV. When the RT distribution was decomposed into its underlying parameters, however, the MDD and Control groups didn't differ in their central tendency or in the SD of the underlying normal distribution. Instead, the MDD group had a significantly larger τ , the component reflecting intraindividual dispersion in responses that creates a skewed, heavy-tailed distribution. Unpacking RT thus showed that depression strongly affected RT variability but not overall speed. As many researchers have argued, skewed RT distributions are inadequately described by only two parameters, such as a mean and SD (e.g., Anders, Alario, & Van Maanen, 2016; Heathcote et al., 1991; Nesselroade & Salthouse, 2004). As the present findings clearly show, an alternate model that represents the distributional form more faithfully can illuminate differences that aren't otherwise apparent.

The present research indicates greater RT variability in MDD, despite mixed and null findings in past research. Our study differed from past studies in some key respects: (1) including only antidepressant-free participants enabled us to examine RT data that were not clouded by the broad and complex effects of antidepressant medications on motivation; (2) model-based ex-Gaussian methods were applied; and (3) a clear incentive was at stake, so reward processes should be engaged. The present task had a predictable structure—all correct

trials were rewarded, with no losses for mistakes—so it would be interesting for future work to explore factors that might influence RT variability, such as different probabilities of reward, penalties for errors, or loss-avoidance tasks, using the broader MDD and motivation literature as a guide (Brinkmann & Franzen, 2015). Indeed, many past studies likely have data suitable for reanalysis using model-based RT methods.

Future work should unpack the mechanisms underneath MDD's effect on RT variability. Although ex-Gaussian parameters lack a unitary interpretation across all contexts (Matzke & Wagenmakers, 2009), in cognitive tasks requiring executive control greater Tau is consistent with occasional lapses in attention (McVay & Kane, 2012; Welhaf et al., 2020). One possibility, then, is simply a broad influence of depression on executive functions (Snyder, 2013), regardless of incentives. Another possibility is that depression may foster "goal neglect," in which the task goal slips in and out of mind (Kane & Engle, 2003). Maintaining a stable representation of the task incentive throughout the task would result in lower RT variability. MDD might thus increase variability via "incentive slips," in which representations of the incentive occasionally lapse, resulting in more dispersed and variable responses. Because the present experiment lacked a no-incentive condition, it is unable to distinguish between a broad, global impairment versus an incentive-specific impairment, but the nearly-indistinguishable patterns for the 3-cent and 15-cent incentive conditions might imply that a global executive effect is more likely (see OSM). These hypotheses thus await future research, and they illustrate the value of decomposing RT performance into underlying components.

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Table 1

Descriptive Statistics

Outcome	MDD		Control	
	<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>
Mean RT	1211.75	77.33	1064.07	42.67
ISD	580.98	54.15	440.73	31.27
CoV	46.76	2.20	39.01	1.51
Mu	659.38	37.01	663.85	21.79
Sigma	104.37	24.55	93.97	9.48
Tau	552.38	53.87	400.23	29.87

Note. MDD $n = 17$, Control $n = 59$. RT = response time; ISD = individual standard deviation; CoV = coefficient of variation.

Figure 1. Illustrations of RT distributions that vary only in their central tendency μ (left) and only in τ (right).

Note. In the first panel, the distributions have identical σ (90) and τ (400) values but vary in μ (400 or 500). In the second panel, the distributions have identical μ (400) and σ (90) values but vary in τ (400, 800).

Figure 2. Boxplots for response times, individual standard deviations, and coefficient of variation for the Control and MDD groups.

Note. The solid line represents the median value; the small jittered dots are the scores for each participant. RT = response time; ISD = individual standard deviation; CoV = coefficient of variation.

Figure 3. Ex-Gaussian model-estimated response time distributions for the Control (white) and MDD (grey) groups.

Figure 4. Estimated ex-Gaussian parameters Mu, Sigma, and Tau for the Control and MDD groups.

Note. The solid line represents the median value; the small jittered dots are the scores for each participant.

Online Supplemental Material

As noted in the main article, these analyses come from a larger NIH-funded study of depression, effort, and motivation. The core of the project involves using impedance cardiography to study autonomic markers of effort in lab-based tasks and in daily life via experience sampling and ambulatory impedance devices. As a result, recruitment entailed additional eligibility criteria related to age, medication use, and cardiovascular health that are not directly related to the RT variability hypotheses.

Note that the sample size of participants for the RT variability analyses will vary from prior analyses because of different reasons for missing data. For example, psychophysiological analyses require exclusions for poor biological signal quality or related issues affecting cardiac outcomes, but the RT variability analyses can include anyone with valid RT data. The following details about recruitment, screening, and participation are taken directly, with minor editing, from the OSM for the project's first publication (Silvia et al., in press).

1. Detailed Description of the Recruitment and Screening of Participants

Participants

We recruited participants via print ads in local media, online Craigslist ads, and flyers distributed around the neighboring cities and the local university campus. Some recruitment materials focused on attracting people who were likely to be experiencing depression; other materials focused on attracting non-depressed, healthy controls. People who contacted the research team (via phone, text, or e-mail) took part in a brief phone interview to screen out obviously ineligible participants.

Clinical screening interview. We conducted 156 phone screenings and invited 88 people to a face-to-face interview and screening session on the university campus. Participants received \$15 in cash for completing this session, which consisted of a structured clinical interview, questions about cardiovascular health and medication use, measurement of height

and weight, and assessment of heart rate and blood pressure. To be eligible, people had to be between 18 and 45 years of age and in good cardiovascular health. People were ineligible if they had ever had a heart attack, stroke, or any heart surgery; if they had ever been to a doctor for any heart issues, such as irregular heartbeats or high blood pressure; if they took any medication to treat any heart or cardiovascular condition, including cholesterol medication; and if they had diabetes, were pregnant, or took daily preventative asthma medication. To rule out hypertensive participants, the interviewer assessed blood pressure and heart rate with an automated monitor and a standard cuff placed over the brachial artery of the non-dominant arm. The sample's mean values were within normal limits (SBP $M = 120.97$ mmHg, $SE = 1.56$; DBP $M = 67.96$ mmHg, $SE = 1.31$; HR $M = 74.31$ bpm, $SE = 1.34$). Height and weight were measured with a medical beam scale. The sample's median body mass index (BMI) was 24.72 ($M = 26.26$, $SE = .75$, range from 17.47 to 47.25), which is on the boundary of normal and overweight.

Participants completed a structured clinical interview administered by trained clinical psychology graduate students using select modules of the Structured Clinical Interview for DSM disorders (SCID-5-RV: First, Williams, & Spitzer, 2015; SCID-II: First, Gibbon, Spitzer, Williams, & Benjamin, 1997). The SCID version for the DSM-5 was released after we began data collection, so the first 21 participants were interviewed with the SCID-IV-TR. The diagnostic criteria for major depression remained the same across the two versions.

Participants were ineligible if they had taken antidepressants within the past 8 weeks. We did not assess why people were not taking anti-depressants, but in our experience with recruiting adults with depression from the local population, we find that the most common reasons are a general reluctance to take prescription medication, intolerance of antidepressant side effects, and the many issues of health-care access and affordability that are unfortunately common in the United States.

In addition, participants were ineligible if they reported any past manic or hypomanic symptoms, reported any clinically significant psychotic symptoms, reported current substance

abuse or dependence, had active suicidal ideation, or met diagnostic criteria for antisocial or borderline personality disorder. After their participation in the study was complete, the clinical interviewer discussed treatment and referral options with participants for whom it was relevant.

Final sample. Based on the screening interview, 78 people who were determined to be eligible ultimately took part in the laboratory part of the study. Of the 78, MDD was ruled “present” in 18 (22.4%) and “not present” in 60 (77.6%). The group sizes were thus unequal, which could have implications for statistical power and effect size interpretation. The sample was predominantly young ($M = 23.26$ years, $SE = .61$, range = 18 to 43) and female ($n = 59$, 75.6%). Based on self-reported race and ethnicity, the sample was diverse: 47.4% African American, 35.9% European American, and 15.4% Hispanic/Latino/a. (People could select more than one category or decline to select any.)

2. Additional Procedure Details

Eligible participants took part in the laboratory session soon after the screening interview, usually within a week. The clinical interviewer set up a time for the participant to take part and explained that for the day of the laboratory session, participants would have to abstain from exercise, physical exertion, caffeine, and nicotine from the time of waking up until the laboratory session. The interviewer went over these issues with the participants to ensure that they understood that caffeine is in many beverages (e.g., often in tea, soda, and energy drinks) and some foods (e.g., caffeinated gum and chocolate) and that abstaining from nicotine refers not only to smoking cigarettes but also to nicotine gums, patches, chewing tobacco, and nicotine delivery systems like vaping and e-cigarettes. Participants were reminded of the scheduled session and the activities to avoid the day before the session. Participants received \$20 plus their task earnings for taking part in the laboratory session. The surveys and cognitive tasks were administered with DirectRT and MediaLab research software. Responses were collected with an Empirisoft high-speed keyboard, which has a timing accuracy of 1 ms.

OSM Table 1

Descriptive Statistics For 3-Cent and 15-Cent Conditions

		MDD		Control	
Incentive	Outcome	<i>M</i>	<i>SE</i>	<i>M</i>	<i>SE</i>
3 cents	Mean RT	1198.99	78.31	1055.78	42.09
	ISD	562.90	57.41	426.20	31.75
	CoV	45.74	2.68	38.12	1.74
	Mu	663.31	48.18	658.08	19.97
	Sigma	108.72	29.70	86.35	6.53
	Tau	535.69	56.74	397.74	32.77
15 Cents	Mean RT	1224.50	91.60	1072.36	47.52
	ISD	599.07	59.90	455.26	34.02
	CoV	47.78	2.37	39.91	1.77
	Mu	655.45	38.42	669.63	35.36
	Sigma	100.02	23.96	101.59	18.05
	Tau	569.07	62.35	402.72	31.03

Note. MDD $n = 17$, Control $n = 59$. ISD = individual standard deviation. CoV = coefficient of variation.

OSM Figure 1. Model-estimated ex-Gaussian RT distributions for the Control (white) and MDD (grey) groups and for the 3-cent (solid) and 15-cent (dotted) incentive conditions.

Note. For the analyses in the main article, the 3-cent and 15-cent blocks were averaged to form an overall score because the findings were essentially identical for the incentive levels (see OSM Table 1). These curves visually depict the lack of differences. The RT distributions in the 3-cent and 15-cent blocks are barely distinguishable for the MDD group (grey curves) and almost wholly overlapping for the Control group (white curves).