Reward-seeking deficits in major depression: Unpacking appetitive task performance with ex-Gaussian response time variability analysis

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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: (a) a sample of adults (n = 78; 18 MDD, 60 control) free of antidepressant medication, (b) an unambiguously appetitive task with appealing incentives at stake, and (c) ex-Gaussian RT modeling, which can unconfound speed and variability by estimating parameters for the mean (Mu) and standard deviation (Sigma) of the normal component and the mean of the exponential component (Tau). The groups had comparable Mu and Sigma parameters, but the MDD group had a significantly larger Tau, 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

Article:

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 (RTs).

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 RTs, consistent with the broader "slowing" that can accompany MDD (Caligiuri & Ellwanger, 2000;

den Hartog, Derix, Van Bemmel, Kremer, & Jolles, 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.

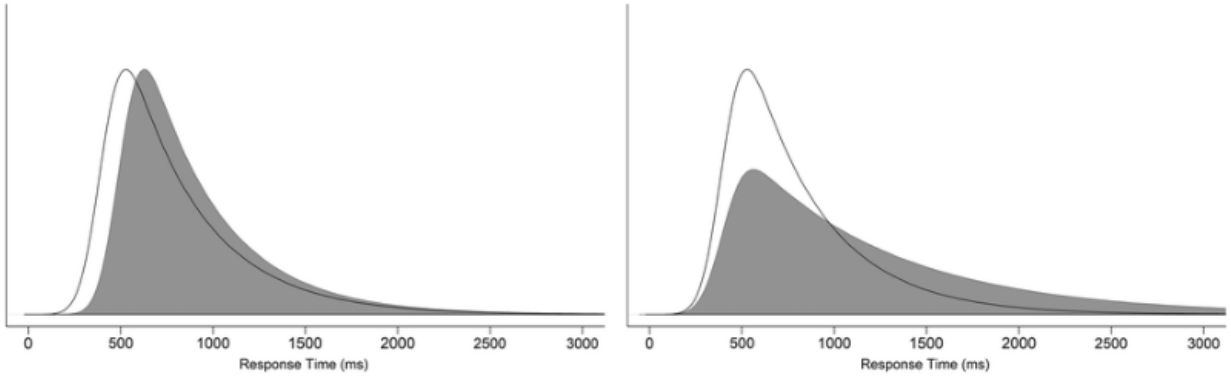

Figure 1. Illustrations of response time distributions that vary only in their central tendency Mu (left) and only in Tau (right). In the first panel, the distributions have identical Sigma (90) and Tau (400) values but vary in Mu (400 or 500). In the second panel, the distributions have identical Mu (400) and Sigma (90) values but vary in Tau (400 or 800).

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: (a) Mu, the mean of the normal (Gaussian) component and the central tendency of the RT distribution; (b) Sigma, the standard deviation of the normal component; and (c) 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, Rombouts, & van Asma,

1996) and CoV (Kaiser et al., 2008) values than healthy controls; conversely, another study found the opposite CoV effect (Chase, Michael, Bullmore, Sahakian, & Robbins, 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., 2019). 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., 2019). 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 materials (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-II: First, Gibbon, Spitzer, Williams, & Benjamin, 1997; SCID-5-RV: First, Williams, Karg, & Spitzer, 2015). 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 two 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 min per block, with a 90-s break—each with a different incentive level manipulated within-person (Harper, Silvia, Eddington, Sperry, & Kwapil, 2018). Based on the block, correct responses earned 3 cents (3c) or 15 cents (15c) each.

Results

Data Preparation

Preparing the RTs for analysis involved (a) omitting incorrect responses (3c: 7.16%; 15c: 6.48%) and (b) omitting RTs smaller than 200 ms (0% omitted) and greater than 5,000 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 3c and 15c incentives (see OSM for details and plots), so the two blocks were averaged. Table 1 displays the descriptive statistics.

Table 1. Descriptive Statistics

	MDD		Control	
Outcome	***M***	***SE***	***M***	***SE***
Mean RT	1211.75	77.33	1064.07	42.67
ISD	580.98	54.15	44.73	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. MDD = major depressive disorder; RT = response time; ISD = individual standard deviation; CoV = coefficient of variation.

Effects on RT 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 RTs 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.

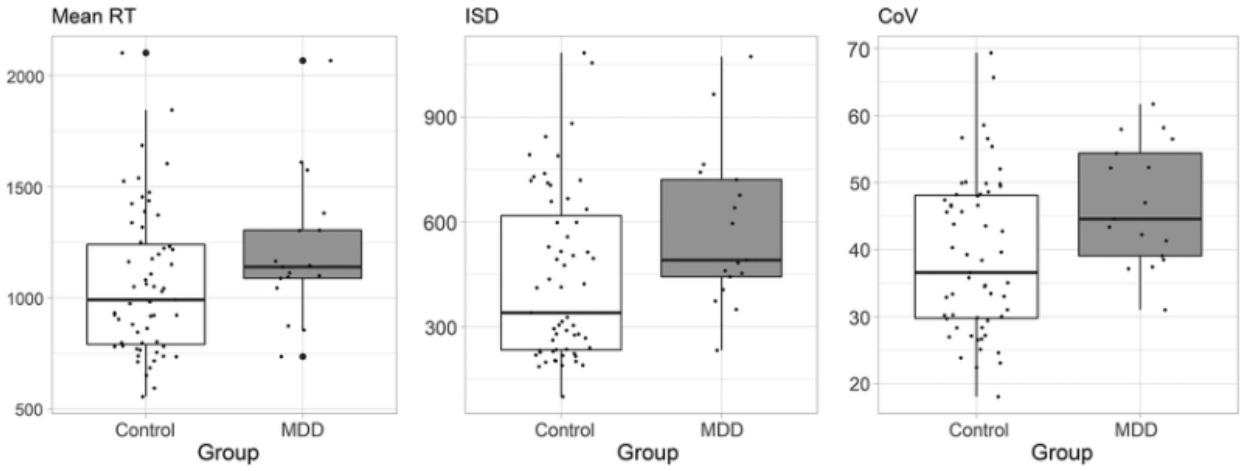

Figure 2. Boxplots for response times, individual standard deviations, and coefficient of variation for the control and MDD groups. The solid line represents the median value; the small jittered dots are the scores for each participant. RT = response time; ISD = individual standard deviation; CoV = coefficient of variation; MDD = major depressive disorder.

Next, we examined parameter estimates of the RT distribution from the ex-Gaussian decomposition. Figure 3 displays the estimated distributions for the control (white) and MDD (gray) conditions. Visually, the two conditions appear to have the same central tendency (Mu), but the MDD condition appears much more variable. Indeed, regression models predicting the ex-Gaussian parameters (see Figure 4) found no difference for the Mu (b = −.03, SE = .26, p = .915) and Sigma (b = .13, SE = .33, p = .686) parameters. The MDD group, however, had a significantly larger Tau (b = .65, SE = .24, p = .007), reflecting greater RT variability.

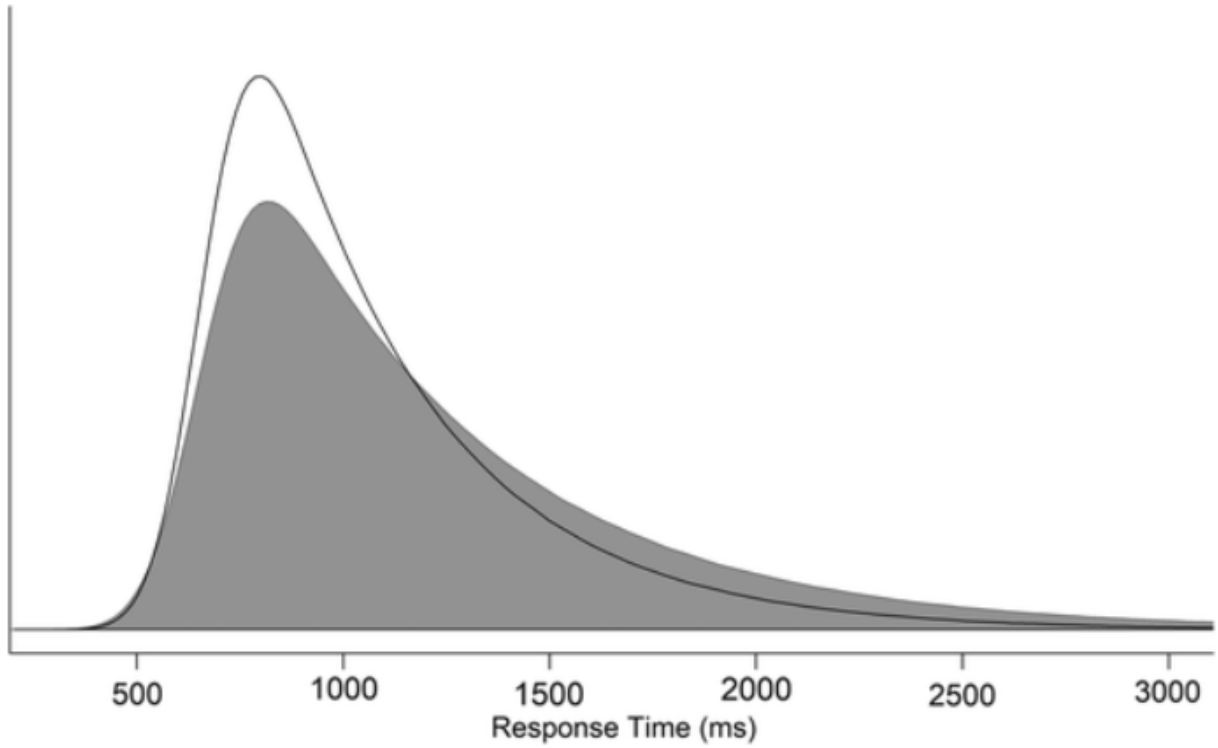

Figure 3. Ex-Gaussian model-estimated response time distributions for the control (white) and major depressive disorder (gray) groups.

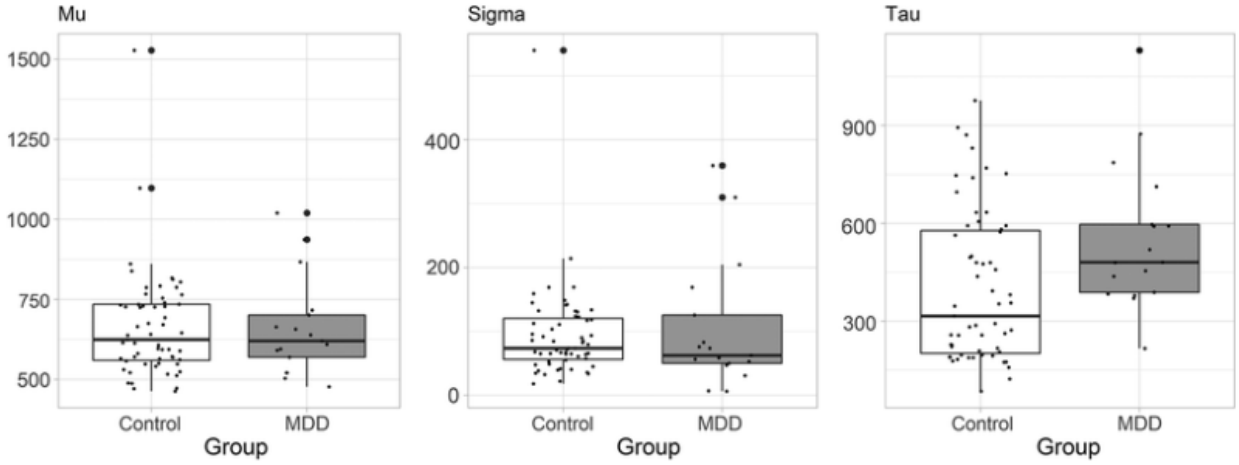

Figure 4. Estimated ex-Gaussian parameters Mu, Sigma, and Tau for the control and MDD groups. The solid line represents the median value; the small jittered dots are the scores for each participant. MDD = major depressive disorder.

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 did not differ

in their central tendency or in the SD of the underlying normal distribution. Instead, the MDD group had a significantly larger Tau, 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 are not 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: (a) 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, (b) model-based ex-Gaussian methods were applied, and (c) 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 3c and 15c 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.

Footnotes

1 The experiment had two between-person counterbalancing factors. First, half of 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.

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