

# Reduced drift rate: a biomarker of impaired information processing in functional movement disorders

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Functional neurological disorder is a common and phenomenologically diverse condition. Resultant disability is caused by both the dominant clinical presentation, e.g. paralysis or tremor and additional symptomatology such as cognitive symptoms. Recently the similarity of neuropsychiatric profiles across a range of functional syndromes has been highlighted. This is suggestive of a common underlying mechanism with a theoretical deficit of information processing proposed. Identification of an experimental biomarker for such deficits could offer novel assessment and therapeutic strategies. In this study, we took the temporal discrimination threshold as a paradigm that can be used to model sensory processing in functional movement disorders. Our hypothesis was that we would be able to delineate markers of slowed information processing in this paradigm removed from the phenomenological presentation with a movement disorder. We recorded both response accuracy and reaction time in a two-choice temporal resolution/discrimination task in 36 patients with functional movement disorders and 36 control subjects. A psychometric function was fitted to accuracy data for each individual revealing both abnormally high threshold values ( $P = 0.0053$ ) and shallow psychometric slopes in patients ( $P = 0.0015$ ). Patients with functional movement disorders also had significantly slower response times ( $P = 0.0065$ ). We then used a well-established model for decision-making (the drift diffusion model) that uses both response accuracy and reaction time data to estimate mechanistic physiological dimensions of decision-making and sensory processing. This revealed pathologically reduced drift rate in the patient group, a parameter that quantifies the quality and rate of information accumulation within this sensory task ( $P = 0.002$ ). We discuss how the deficits we observed in patients with functional movement disorders are likely to stem from abnormal allocation of attention that impairs the quality of sensory information available. Within a predictive coding framework sensory information could be down-weighted in favour of predictions encoded by the prior. Our results therefore offer a parsimonious account for a range of experimental and clinical findings. Reduced drift rate is a potential experimental marker for a generalized deficit in information processing across functional disorders that allows diverse symptomatology to be quantified under a common disease framework.

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## Introduction

Functional neurological disorder is a common source of disability in medicine with varied clinical presentations. For many years diagnostic labels (hysterical, psychogenic, conversion disorder) and explanations separated these patients from the neurological sphere (Edwards *et al.*, 2012). However, such a dualistic approach is neuroscientifically suspect, maps poorly to clinical manifestations, and has left this patient group poorly served by healthcare professionals and vulnerable to iatrogenic harm (Nielsen *et al.*, 2019). In recent years the term ‘functional neurological disorder’ has (re)gained traction (Carson *et al.*, 2012; Edwards *et al.*, 2014; Espay *et al.*, 2018) and greater understanding of these disorders has been achieved through clinical observation, experimental investigation and directed rehabilitation (Nielsen *et al.*, 2015, 2017). Aetiological frameworks of functional disorders highlight that multifactorial biopsychosocial substrates can lead to symptoms (Parees *et al.*, 2014; Espay *et al.*, 2018). However, the final neurobiological mechanism is thought to be more homogenous across patients, with two common axes of dysfunction proposed: misdirected attention and abnormal predictive processing (Edwards *et al.*, 2012; Parees *et al.*, 2013; McIntosh *et al.*, 2017; Van den Bergh *et al.*, 2017).

The disability associated with functional disorders is often compounded by additional symptoms across body systems that are thought to stem from the same neurobiological vulnerabilities. For example, common neuropsychological symptoms are seen across a range of functional syndromes such as fibromyalgia, chronic fatigue syndrome and functional neurological syndromes with theoretical deficits in attention and slowed information processing proposed (Teodoro *et al.*, 2018). Such findings suggest there should be viable biomarkers; however, standard objective cognitive testing frequently reveals a discordance with subjective symptoms (Teodoro *et al.*, 2018). Identifying quantifiable tools for the assessment of abnormalities in cognitive processing in functional disorders is therefore an unmet research need and if available could have multiple applications in clinical and rehabilitative practice.

Despite a move towards unifying disease models for functional disorders, experimental findings are often interpreted in isolation. For example, the temporal discrimination threshold is elevated in functional dystonia and functional tremor (the shortest interstimuli interval where an individual can recognize that two stimuli are asynchronous) (Fig. 1A and B) (Morgante *et al.*, 2011; Tinazzi *et al.*, 2014). However, the temporal discrimination threshold is also elevated in other subtypes of dystonia and other movement disorders such as Parkinson’s disease. This non-specificity is suggestive of a composite

metric within which disease-specific abnormalities could be concealed.

We were therefore interested in using the known psychophysical abnormality in temporal discrimination as a broader model of brain function and information processing in functional disorders. Our hypothesis was that we would be able to delineate markers of dysfunctional cognitive processing in this paradigm removed from the phenomenological presentation within our patient group presenting with a functional movement disorder. Using a randomized and automated version of the temporal discrimination task we recorded both response accuracy and reaction time in order to utilize a well-established model for decision-making (the drift diffusion model). After confirming the temporal resolution deficit we were then able to estimate novel physiological dimensions of decision-making and sensory processing (Fig. 1C and D) to reveal a potential biomarker for impaired cognitive processing in functional disorders.

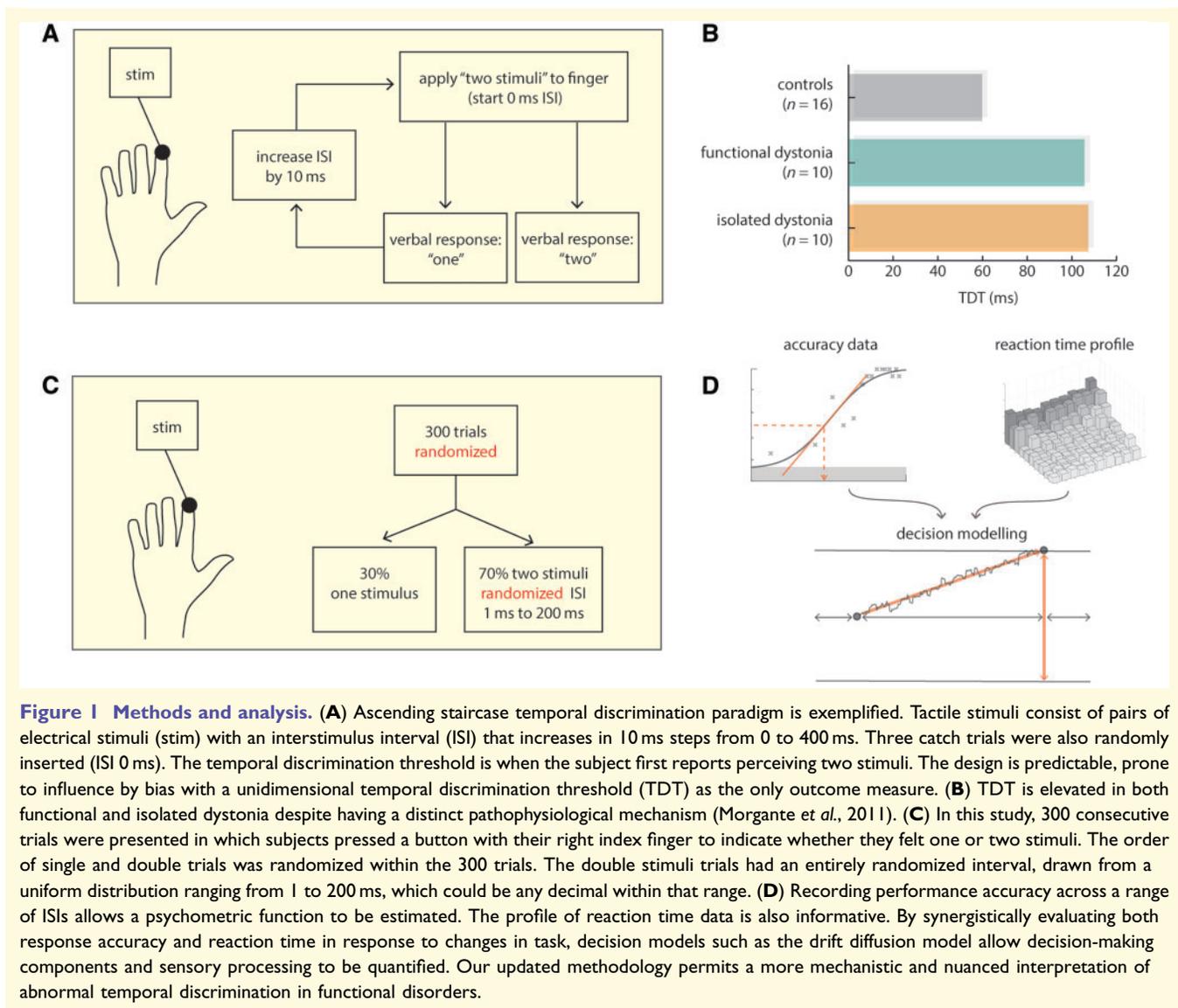
## Materials and methods

### Participants

Thirty-six patients with functional movement disorders were recruited consecutively from a specialist neurology clinic for functional movement disorders. Patients had a variety of subtypes of functional movement disorders (Supplementary Table 1). Diagnosis was made by an expert in functional movement disorders (M.J.E.) and in all patients a neurological examination was performed to exclude significant cognitive or upper limb sensory deficits. Thirty-six age, sex and intelligence matched healthy control subjects were also recruited. Intelligence was estimated by the non-verbal Raven matrix score (maximum/high performance score 12) (Raven, 2000). We also recorded: the duration of patient’s disease in years, estimated disability (SF-36 Physical Functioning domain, 0 = maximal disability, 100 = no disability) (Ruta *et al.*, 1993), anxiety and depression (Hospital Anxiety and Depression Scale, separately scored for anxiety and depression) (Zigmond and Snaith, 1983) and fatigue symptoms (Fatigue Severity Scale) (Krupp *et al.*, 1989). Written informed consent was obtained and the study was approved at the local Research Ethics Committee.

### Temporal resolution task

The temporal resolution task is a randomized and automated version of previously reported temporal discrimination methods. Resolution is perhaps the more appropriate psychophysical term for this task, which examines the ability to detect that two stimuli are present rather than one. Three hundred consecutive trials were presented, in which subjects pressed one of two buttons with their right index finger, to indicate whether they felt one or two stimuli (Fig. 1C). Unknown to



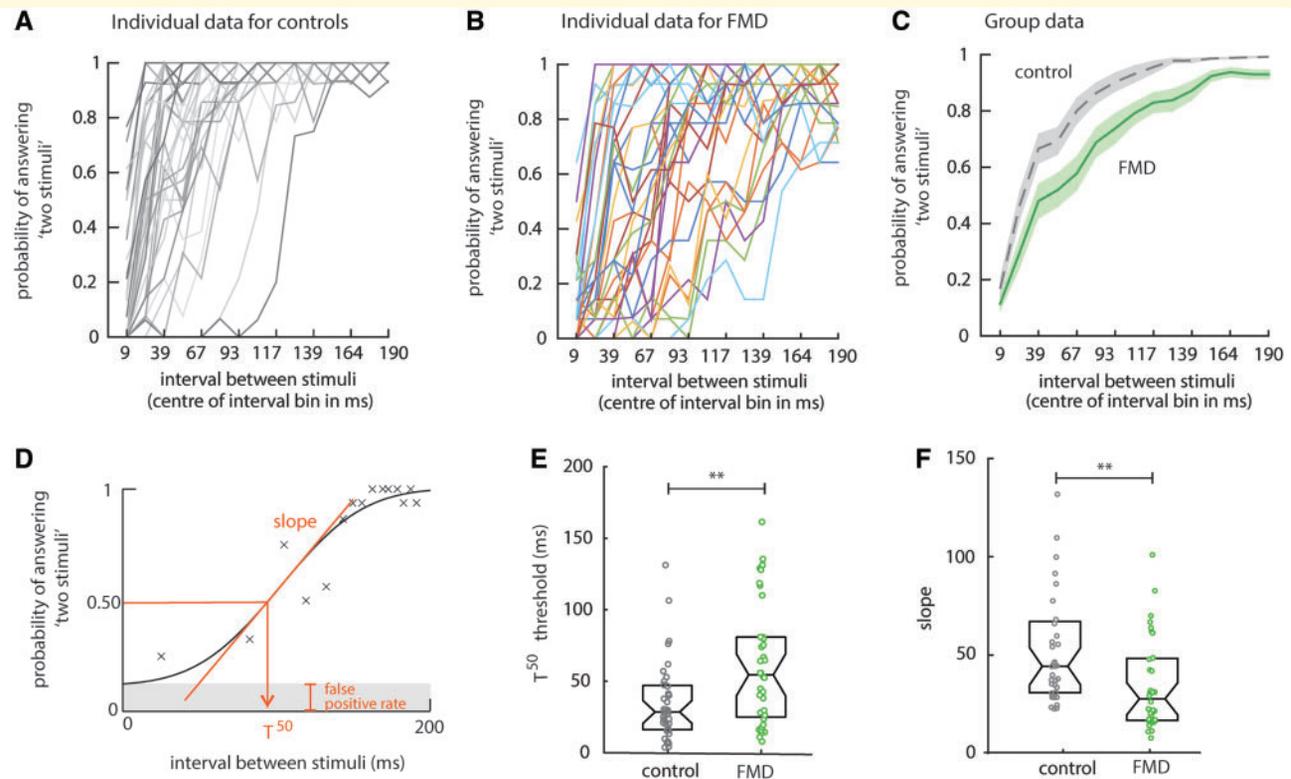
participants, the proportion of single stimulus trials was 30% and of double stimulus trials was 70%. On double stimulus trials, the interval between the two stimuli was randomized, drawn from a uniform distribution ranging from 1 to 200 ms that could take any decimal value within that range. The order of single and double trials was also randomized within the 300 trials. The tactile stimuli were delivered to the index finger of the left hand, using a ring electrode connected in parallel with two Digitimer electrical stimulators (Sadnicka *et al.*, 2017). A single side was tested as previous studies have shown that thresholds are elevated in both hands with no difference between affected and unaffected sides (Morgante *et al.*, 2011; Tinazzi *et al.*, 2014). An answer was required for every trial and subjects were prompted to guess if they paused longer than 5 s (forced choice). Subjects were trained in the task using 20 sample trials (data not analysed) and then performed the 300-trial task. The total length of time of the experiment was ~15 min. Experiments were coded in MATLAB using the Cogent toolbox. All participants were able to complete the 300 trials of the task.

## Outcome measures and psychometric analysis

Accuracy of response and reaction time were recorded for each trial. A psychometric function was fitted to accuracy data for each individual (Fig. 2D). Two stimuli data were binned into 15 interval groupings spread evenly over the range of possible intervals. The psychometric function used the cumulative Gaussian ( $\Phi$ ), a mathematical function of sigmoid shape:

$$y = \Phi\left(\frac{(\log(x) - \mu)}{\sigma}\right) \times (1 - FP) + FP \quad (1)$$

where  $y$  is the proportion of responses on which ‘two stimuli’ were perceived, and  $x$  is the interval duration. The false positive rate (percentage of one stimulus trials incorrectly identified as two-stimulus trials, FP) defined the floor of the function. The temporal resolution threshold ( $\mu$ ) was defined as the interval at which the probability of either answer is equal ( $T^{50}$ ). The slope of the function at  $T^{50}$  is equal to the inverse of the standard deviation ( $1/\sigma$ ) of the response distribution



**Figure 2** Reduced response accuracy in functional movement disorders. (A) Individual data points over 15 interval bins linked by line in the control group (greyscale) and (B) patients with functional movement disorders (FMD). (C) Group mean and standard error (shaded) of each group. (D) The psychometric function (solid black line) and its main outcome metrics of  $T^{50}$  and slope are exemplified with binned single dataset shown by crosses. Box plots of (E) temporal resolution threshold ( $T^{50}$ ) in ms and (F) slope. The median and interquartile range are indicated by horizontal lines of boxes with individual data values for controls (grey circles) and patients (green circles). \*\* $P < 0.01$ .

and gives a measure of the range of time intervals over which decisions were uncertain. The psychometric function fitted the responses of all participants well (Supplementary Fig. 1). Akaike's Information Criterion (AIC) was used to evaluate the fit of the psychometric model for each subject. This takes into account both the statistical goodness of fit (log-likelihood) and penalizes for an increasing number of parameters ( $k$ ) estimated to achieve that degree of fit.  $AIC_{model}$  was compared to a model of guessing (with a mean AIC of 207.9) with lower values indicating the preferred model. The mean  $AIC_{model}$  was 107.1 supporting that the psychometric function predicted the individual participants' choices well. Reaction time was the time that elapsed (in seconds) from stimulus presentation until a button press.

## Drift diffusion model

Accuracy and reaction time data were then modelled using the drift diffusion model, which is a model of the cognitive processes involved in simple two-choice decisions. It separates the quality of evidence entering the decision from the decision criteria and other non-decision processes such as stimulus encoding and response execution (Ratcliff and McKoon, 2008). Mathematically, the distribution of reaction times and errors provides an estimate of the rate of information accumulation (drift rate) and the decision boundary. The basic

assumption is that, in order to make a speeded choice between two options, evidence is accumulated sequentially over time during the decision period (Fig. 4A). As soon as sufficient evidence towards one option or the other has been collected, the process stops and a response is initiated. The accumulation process is governed by two distinct forces: the tendency to drift towards either decision boundary (drift rate) and a stochastic component (diffusion, i.e. random noise). The distance between the two boundaries (decision boundary) reflects the amount of evidence required before a decision is made. The bias, or starting point, reflects the general tendency to report one response alternative over the other. We modelled decisions as bias-free, as the proportion of choices of the 'one stimulus' and 'two stimuli' response options was approximately equal, and the randomized trial order meant that having a bias would not yield any advantage. We initially allowed non-decision time (sum of time taken for sensory encoding of stimuli and motor response) to vary but as there was no difference between groups and the model did not fit the data better, this was subsequently fixed at 100 ms. To determine the effect of decision difficulty on responses, four additional competing diffusion models were fitted and compared using the AIC (Supplementary Table 2). Model 2, in which drift rate varied across conditions but decision threshold was fixed, was the optimal model. This is in line with the task design: as difficulty of decision varied, drift rate also varied; the decision criterion

was not experimentally varied, and accordingly the boundary separation was constant (i.e. no change in emphasis of task instruction, reward contingency etc.). All subjects were adequately fitted by the model [as defined by AIC values < 3 standard deviations (SD) from mean].

## Statistical analysis

To compare distributions between groups, independent *t*-tests were calculated when the data were normally distributed and the two-tailed Wilcoxon rank sum test for independent samples ( $W_m$  = rank,  $P$  = significance level,  $z$  = effect size) was used otherwise. A linear mixed effects model was fitted to reaction time data using a maximum likelihood method (*t*-statistic and significance level reported). Repeated measures ANOVA across condition was used to compare the drift rate between groups (*F*-statistic and significance level reported). Spearman's rank correlation coefficient was used to estimate the association between continuous variables ( $\rho$  and significance level reported). One-way ANOVA was used to compare means across subtypes of functional movement disorders (dystonia, myoclonus, tremor, tics, weakness, 'other') with the Greenhouse-Geisser correction applied as the assumption of sphericity was violated [as four comparisons were made the significance level was  $P = 0.0125$  (0.05/4)]. Data analysis and statistics were performed using MATLAB (MathWorks Inc., Natick, MA, USA) and SPSS (IBM SPSS Statistics, Armonk, NY, USA).

## Data availability

The data that support the findings of this study are available from the corresponding author, upon reasonable request.

## Results

### Patients have prolonged thresholds and poor discrimination over a wide range of intervals

In all participants, the probability of reporting 'two stimuli' increased as the interval between stimuli increased and discrimination became easier (individual binned data for controls and patients shown in Fig. 2A and B). At the group level, patients clearly demonstrated impaired discriminatory ability (Fig. 2C). For each subject, a psychometric function was fitted to response behaviour to quantify this difference (Fig. 2D). The temporal resolution threshold ( $T^{50}$ ) was defined as the interval at which subjects responded 'two stimuli' in half of the trials (i.e. probability of answering 'two stimuli' is 0.5). The slope of the function at  $T^{50}$  was also calculated and gives a measure of the range of time intervals over which decisions were uncertain. A steep slope indicates a small range in which answers are uncertain, a shallow slope indicating a broader range. These metrics are complementary to each other, reflecting different elements of response behaviour and both were abnormal in patients with functional movement disorders. The threshold value,

$T^{50}$ , was significantly elevated signifying that patients required a longer interval between stimuli before they could discriminate two stimuli (Fig. 2E, controls median = 37.2 ms, functional median = 53.0 ms, two-tailed Wilcoxon rank sum test for independent samples:  $W_m$  = 1066,  $P = 0.0053$ ,  $z = -2.78$ ). In addition, the slope was shallower in these patients (Fig. 2F, control median = 43.4, functional median = 26.9,  $W_m$  = 1597,  $P = 0.0015$ ,  $z = -3.18$ ) signifying that there was response uncertainty and variability of the accuracy of response over a wider range of intervals. The false positive rate, which defined the floor of the psychometric function, was equivalent across groups (controls median = 2.5%, functional median = 2.2%,  $W_m$  = 1275,  $P = 0.66$ ,  $z = -0.44$ ).

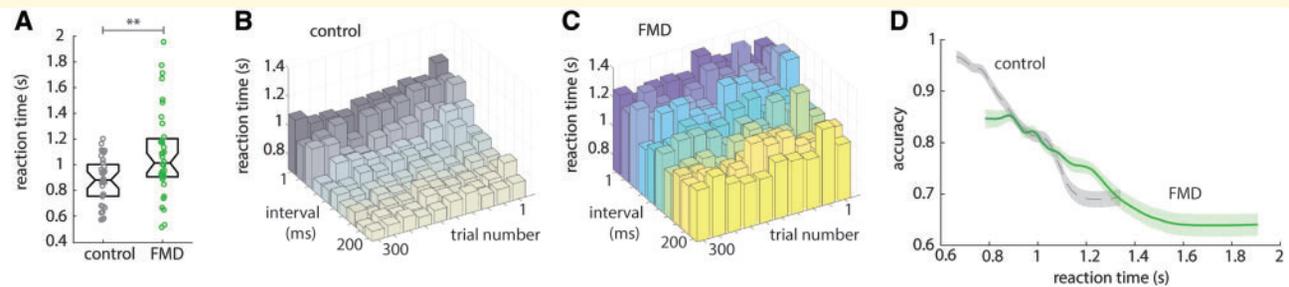
### Patients with functional movement disorders have prolonged and abnormal reaction time profiles

Patients with functional movement disorders also had significantly slower response times (Fig. 3A) (median reaction time across all 300 trials: controls = 0.88 s, functional = 1.01 s,  $W_m$  = 1072,  $P = 0.0065$ ,  $z = -2.71$ ). In addition, reaction time data did not vary with difficulty and practice in the same way as controls. First, healthy control subjects responded faster when decisions were easier whereas this effect was reduced in patients (Fig. 3B and C) [Group  $\times$  Interstimulus interval interaction  $t(6206) = 2.26$ ,  $P = 0.023$ ]. Second, controls responded faster over the course of the task, with practice whereas patients improved only weakly and inconsistently [Group  $\times$  Time on task interaction,  $t(6206) = 1.477$ ,  $P = 0.14$ , not significant].

### Elevated reaction times in patients are driven by increased decision uncertainty

A comparison of the proportional accuracy and reaction time data by group (Fig. 3D) highlights an important feature: at comparable levels of accuracy the reaction time was approximately equivalent. This suggests that in patients with functional movement disorders, their slow response times are explainable in terms of uncertainty as it was only during trials in which accuracy was reduced, a marker of trial difficulty, in which reaction time was prolonged. A larger proportion of trials were at low levels of accuracy and corresponding prolongation of reaction times beyond that of the control group. Patients also did not match the high-end performance of controls.

In summary, in patients with functional movement disorders, reaction times were significantly slower, and failed to conform to control patterns of change in response to increasing interval between stimuli. However, at equivalent levels of response accuracy there was little to separate reaction time suggesting that response uncertainty was the main driver of the prolongation of reaction time.



**Figure 3** Abnormal reaction time profiles in functional movement disorders. **(A)** Median reaction time across all 300 trials was significantly higher in patients. Box plot shows median and interquartile ranges by horizontal lines, individual values plotted as circles. **(B)** 3D plot with reaction time shown on the y-axis and both trial number (x-axis) and interval (z-axis) varied on the lower axes. Control data shown in greyscale demonstrating a clear gradient in reaction time across both variables such that reaction time decreased as both ease of decision (longer interval) and familiarly with task increased (trial number increased). **(C)** The same plot in patients with functional movement disorders reveals that in addition to a general increase in reaction time, the ability to respond faster as interval increased and decisions were easier was reduced. **(D)** Proportional accuracy (y-axis) against reaction time (x-axis) for controls (grey dotted line) and functional movement disorders (green solid line) is plotted with shaded standard error. At comparable levels of response accuracy there was little to separate the groups. Overall individuals with functional movement disorders had worse response accuracy with longer reaction times. FMD = functional movement disorder. **\*\*** $P < 0.01$ .

## Abnormal sensory evidence accumulation in functional movement disorders

The patterns of change seen in patients with functional movement disorders both in terms of accuracy and reaction time were highly suggestive of a deficit in the quality of sensory information informing their choice on each trial. To investigate this, we fitted the drift diffusion model to data. The diffusion model examines both sensory stimulus encoding ability and decision processes such as the decision criterion by evaluating accuracy and reaction time distribution data in synergy. It measures two key properties of decision-making: the drift rate, indicating the rate of accumulation of information that is determined by the quality of information extracted from the stimulus; and the decision boundary, indicating how much evidence one requires before a decision is made (Fig. 4A). To model the data, trials were divided into five interval bins and the drift rate was defined as the tendency to drift towards response option ‘two stimuli’. Thus, at the lowest interval bin, drift rates were negative as the intervals presented on these trials were subthreshold and the response option ‘one stimulus’ was reached.

Modelling data using the drift diffusion model showed that the rate of evidence accumulation was systematically lower in patients with functional movement disorders (Fig. 4B) [repeated measures ANOVA between-subject effect of group  $F(1,7) = 10.1$ ,  $P = 0.002$ , Drift  $\times$  Group  $F(1.4,100.3) = 3.842$ ,  $P = 0.038$ ]. Rates only approximated each other in the second interval bin, which was close to the point of the resolution threshold/perceptual equivalence and thus drift rates were close to zero in both groups. Importantly the modelled drift rates across the five bins of decision difficulty showed remarkably strong consistency

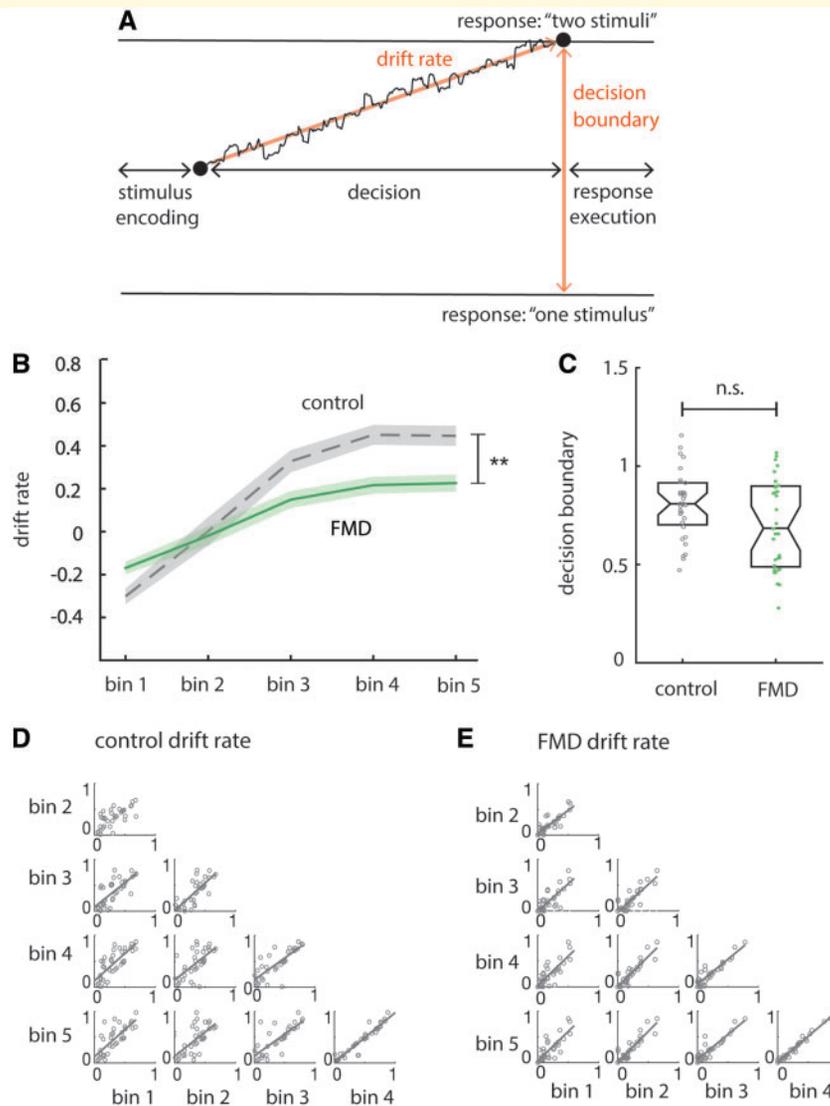
within subjects (Fig. 4D and E) (all  $\rho > 0.6$ , all  $P < 0.001$ ). Therefore, if an individual has a higher rate of information accumulation in one subset of trial difficulty, then they also had a higher rate, relative to other individuals, in the other difficulty levels. This suggests that the drift rate for an individual is a powerful marker of their performance across all trial difficulties.

The decision boundary, which quantifies the amount of evidence required before a decision is made, was the same across groups (Fig. 4C,  $W_m = 1396$ ,  $P = 0.35$ ,  $z = 0.918$ ). We also looked at markers of variability across groups as a possible proxy for fluctuating attention within the functional group. However, markers such as the standard deviation of drift rate were equivalent across groups ( $W_m = 1421$ ,  $P = 0.23$ ,  $z = 1.19$ ).

## Relationship of findings to demographic variables

We explored whether demographic variables such as disease duration and disability (SF-36), depression, anxiety and fatigue were related to the abnormal drift rate. All correlations were null (Supplementary Table 3), which is evidence that drift rate may be a unifying marker of functional pathophysiology, rather than simply being driven by psychological co-morbidities.

Segregation of patients by subtype of functional motor symptom (e.g. dystonia, tremor) did not reveal unique patterns of abnormalities for a particular phenomenology [one-way ANOVA, significance level = 0.0125 (0.05/4 comparisons): threshold  $F(5,30) = 0.72$ ,  $P = 0.61$ , slope  $F(5,30) = 2.55$ ,  $P = 0.05$ , reaction time  $F(5,30) = 0.41$ ,  $P = 0.84$  and mean drift rate  $F(5,30) = 1.51$ ,  $P = 0.21$ ]. This suggests that similar performance metrics and decision-making are observed across groups, supporting the



**Figure 4 Results of drift diffusion model.** (A) Theoretical illustration of the drift diffusion model. Evidence accumulation leads to a drift towards either of the responses (in this task ‘one stimulus’ or ‘two stimuli’). The rate of information accumulation is defined by the drift rate. The decision boundary is the amount of evidence required before a decision is reached and quantifies the decision criterion settings, which are determined by factors such as instruction and reward contingencies. Non-decision processes such as stimulus encoding and response execution are also isolated. (B) Interval trials were divided into five equal-sized bins of differing trial difficulty numbered 1–5 on the x-axis. Drift rate was impaired in patients with functional movement disorders (FMD) with lower rates of drift across interval bins. (C) The decision boundary was equivalent for controls and FMD. Modelled drift rates were highly consistent within individuals as revealed when drift rates for separate bins were correlated in (D) controls and (E) FMD with all  $\rho > 0.6$  and all  $P < 0.001$ . Therefore, if an individual has a higher rate of information accumulation in one subset of trial difficulty, then they also have a higher rate, relative to other individuals, in the other difficulty levels.

notion that a homogenous pattern of change within this task is seen across phenotypes.

## Discussion

In this study we explored a psychophysical abnormality in temporal discrimination as a broader model of brain function and information processing in functional disorders. In agreement with previous studies, we first confirmed that patients with mixed types of functional movement disorder

have elevated temporal discrimination thresholds. Fitting psychometric functions to data showed both elevated threshold values and also shallower psychometric slope values as patients’ responses were less accurate and less sensitive to changes in the stimulus. In addition, reaction times were significantly slower in the patient group and failed to conform to control patterns of change in response to increasing interval between stimuli. However, at equivalent levels of response accuracy there was little to separate reaction time suggesting that response uncertainty was the main driver of the prolongation of reaction time. Modelling

these data synergistically using the drift diffusion model revealed that the mechanism behind these shifts in performance in functional disorders was a significant reduction in drift rate, an impairment in the quality of the information that drives decision processes.

We were therefore interested in how the reduction in drift rate could be best understood in terms of current neurobiological models of functional movement disorders in which misdirected attention and abnormal predictive processing have been implicated. First, low drift rates could occur if incoming sensory information were gated out or filtered by attentional mechanisms. In functional disorders, abnormal body-directed attentional focus that maintains and monitors functional symptoms is likely to compete with other uses for attentional resources. Pauses and transient resolution of functional tremor during distraction is an example of an abnormal investment of attentional resources towards the abnormal movement in individuals with functional movement disorders (Espay *et al.*, 2018). When a judgement within a sensory task is required, decision-making typically involves deployment of attention to gather information before a decision is made (Hunt *et al.*, 2018). Quantitative assessment of this process is difficult, but interference in decision-making from distraction in healthy people (e.g. dual task procedures), clearly demonstrates the role of attentional resource allocation in decision-making (Logan, 2004; Huang-Pollock *et al.*, 2012; Mittner *et al.*, 2014). Thus, one explanation, either alone or in part, for the deficit we observed in patients with functional movement disorders is that abnormal allocation of attention impairs the quality of sensory information available.

In addition to abnormal attention, functional disorders are also frequently discussed within neurobiological theories termed ‘active inference’. In such models, information flow occurs in two directions: ‘bottom-up’ data from sense organs (e.g. proprioceptive input) and ‘top-down’ predictions from the cortex (called ‘priors’). The brain is then considered a hierarchical structure and at multiple levels statistical comparisons occur by which the individuals try to minimize the difference between these two converging information sources by taking into account their assigned weightings or probabilities (Edwards *et al.*, 2012). In functional disorders, it is thought that abnormally strong and precise priors are formed that drive both symptomatology and the lack of ownership or agency patients experience over their symptoms (Edwards, 2017). Thus, within a predictive coding framework ‘bottom-up’ sensory information would tend to be down-weighted in favour of ‘top-down’ predictions, reducing the quality of sensory information available to the individual during a decision-making task. This theory links conceptually to the psychological construct of dissociation: a disconnection between sensory input and the mental experience of that input (Brown and Reuber, 2016). Other experimental findings that support such a disconnection is the finding of higher pain tolerance in functional dystonia (Morgante *et al.*, 2018), and

functional neuroimaging studies demonstrating hypoactivation of contralateral basal ganglia and thalamus to vibratory stimulation in people with unilateral functional sensorimotor loss that normalized with recovery of symptoms (Vuilleumier *et al.*, 2001).

The temporal resolution task is not immediately connected, phenomenologically, to the main symptoms in our patients—a movement disorder. Therefore the finding that the quality of sensory information driving temporal decisions is reduced consistently in patients is an important observation. Our data also showed that drift rate was remarkably consistent within individuals with high correlations seen between drift rates estimated for different levels of trial difficulty (Fig. 4D and E). Furthermore, in experiments in healthy control subjects, drift rate (and other drift diffusion parameters such as decision boundary) for individuals show significant correlations across a range of tasks testing different cognitive domains (Ratcliff *et al.*, 2006). This needs to be specifically confirmed in patients with functional disorders but supports the hypothesis that the difference in drift rate seen in the functional group in this temporal discrimination task could extend into other two-choice tasks in different cognitive domains. Thus, a slowing of information processing could predispose to diverse symptomatology and dysfunction over different cognitive domains within the brain. For example, clinically, such an abnormality could account for generic cognitive abnormalities, which have been documented across subtypes of functional disorders (Teodoro *et al.*, 2018).

Importantly, the diffusion model can also be used to integrate neural and behavioural datasets. For example, in monkeys, across a range of decision-making scenarios, modelled evidence accumulation correlates closely with the average firing rate of neurons in perceptual and motor brain area (Ratcliff *et al.*, 2003; Brody and Hanks, 2016). Similarly, human frontoparietal networks have been proposed to be responsible for selection and accumulation of information relevant to human decisions (Siegel *et al.*, 2015; Murray *et al.*, 2017). Abnormalities in these circuits may arise in patients with functional disorders and their nature can be informed non-invasively by characterizing psychophysical abnormalities as in this study.

Alternative explanations for our results were also considered and evaluated. For example, we do not believe that the results were secondary to a general lack of engagement in the task by patients. If task engagement were reduced we would expect an increase in lapse rate—that is, incorrect responses should occur not only for the difficult trials, but also the easy ones. This was not seen when individual data were plotted (Supplementary Fig. 1) and indexes for lapses such as false positive rate (single stimulus trials incorrectly identified as two stimuli) were not significantly different between groups. Similarly we believe the profile of data would be very hard to simulate as patients would need to selectively make errors and respond slower when there was uncertainty about whether they experienced one or two stimuli. We also looked specifically for

evidence of unpredictable influences, which would result in variability of performance markers across trials. In support of our interpretation, the estimate of trial-by-trial variability of drift rate was also equivalent across groups. Finally, the other major parameter derived from drift diffusion models is the decision boundary. This parameter is set by the participants' decision-making criterion, which is modulated by many factors such as task instruction and reward contingencies that were not systematically varied within this task. We found that the decision boundary was normal in individuals with functional movement disorders, emphasizing that within this task, which was contextually removed from the patients' symptoms, patients approached decision-making with a similar decision criterion to control subjects.

The temporal discrimination paradigm remains an interesting field of study as thresholds are non-specifically elevated in Parkinson's disease, dystonia and other movement disorders. An expanding literature therefore uses decision models to break down response behaviour into its isolated components so that they can be individually studied. To date, this approach has revealed disease-specific mechanisms for impairments in temporal discrimination that integrate well with existing pathophysiological frameworks. For example, timing deficits in Parkinson's disease cannot be solely attributed to perceptual temporal distortions, but are also associated with impaired use of prior information to inform decisions and with impulsive decision strategies (Zhang *et al.*, 2016; Tomassini *et al.*, 2019). Similarly, modelling perceptual decisions in cervical dystonia points to a conservative decision strategy in cervical dystonia with patients requiring greater time to make decisions because of a wider decision boundary (Sadnicka *et al.*, 2017). This study therefore complements this literature as it offers a novel mechanism behind elevated temporal thresholds in functional disorders.

There are many questions that lead on from our study. The extent and generalizability of the abnormalities in drift rate across cognitive domains can be defined experimentally. For example, do patients have difficulty shifting attention towards bodily sensation as in this task but no deficit in, for example, a visual task with an external focus? Exploring the clinical utility of our finding is also important. For example, could rehabilitation be mirrored by improvements in information accumulation and could drift rate be a useful marker of the severity of symptoms in functional syndromes with non-motor presentations? Specialist physiotherapy is often guided by a visible motor deficit. It would also be helpful to experimentally link abnormalities in drift rate with volitional action, by for example, measurement of perceptual gating and action selection.

In conclusion, our results offer a parsimonious account for a range of experimental and clinical findings. Reduced drift rate is a potential marker for neurobiological deficits within functional disorders allowing diverse symptomatology to be quantified under a common disease framework.

Our work aims to stimulate treatment models in which therapeutic strategies are shared across previously separated disciplines.

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## Competing interests

The authors report no competing interests

## Supplementary material

Supplementary material is available at *Brain* online.

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