**Gamification of Two Alternative Forced Choice:
Validation based on Drift Diffusion Model and Individual Differences**

Esin Turkakin¹, Ceyla Karamanci¹, Kaan Karamanci¹, Fuat Balci^{1*}

¹ Koç University, Department of Psychology, Rumelifeneri Yolu, Sarıyer, Istanbul, 34450, Turkey

* Corresponding Author:

Fuat Balci

Associate Professor

Department of Psychology, Koç University

Rumelifeneri Yolu, Sarıyer, Istanbul, 34450

Turkey

Tel: +902123381130

Email: fbalci@ku.edu.tr

Homepage: <http://tmdmlab.ku.edu.tr>

ABSTRACT

Two alternative forced choice (2AFC) paradigms, coupled with the unified analysis of accuracy and response times within specific decision theoretic frameworks, have provided a wealth of information regarding decision-making processes. One problem of associated experimental tasks is that they are typically not engaging and do not contain stimuli or task representations familiar to participants, resulting in contaminants in the data due to boredom and distraction. Furthermore, when investigating decision strategies, use of noisy stimulus attributes result in undesired variance in the perceptual process complicating the analysis and interpretation of results. To address these fundamental issues, we developed a 2AFC soccer game in which participants' task is to score goals by making leftward or rightward shots after observing the trajectory of the goalkeeper within a trial. The goalkeeper's location is repeatedly sampled from a normal distribution with a constant variance and a mean either to the left or right of the midpoint. We tested participants on three difficulty levels parameterized by the distance between the two means and expected the rate of evidence integration to decrease with increasing difficulty and after errors as characteristic of standard 2AFC tasks. Drift-diffusion model provided good fits to data, and their outputs confirmed our predictions outlined above. Furthermore, we found the evidence integration rates to be negatively correlated with individual differences in maladaptive perfectionism, but not in anxiety or obsessive-compulsive traits.

Keywords: gamification, HDDM, decision making, perfectionism, individual differences

INTRODUCTION

Two Alternative Forced Choice (2AFC) tasks have been vastly used in the behavioral and neurophysiological study of decision making (e.g., Balci et al., 2011; Gold & Shadlen, 2007). In these tasks, participants simply choose one option or the other based on the information available to them in a given trial. These studies have greatly benefited from the application of computational models that allow the estimation of decision process parameters (Forstmann, Ratcliff, & Wagenmakers, 2016). One of the signature models among these is the Drift Diffusion Model (DDM) (Ratcliff, 1978; Ratcliff & Rouder, 1998; Ratcliff & McKoon, 2008). In DDM, a decision is conceptualized as evidence accumulated in a noisy fashion over time (drift), until the accumulated evidence hits one of the two thresholds that represent one of the options (decision boundary) (Ratcliff & Rouder, 1998). DDM allows a deeper understanding of the decision process, by utilizing the basic elements of the performance (e.g. response time (RT) and responses) in a unified fashion (in contrast to their isolated analyses) to characterize the decision performance in terms of psychologically meaningful latent variables of the presumed generative process: cautiousness (i.e threshold setting), evidence gathering efficiency/difficulty of task (i.e. drift rate), prior tendency towards one of the responses (i.e. decision bias), and delay unrelated to the decision process (i.e. non-decision time) (Forstmann et al., 2016).

Many of the tasks in experimental psychology require participants to complete long, repetitive, and relatively dull tasks with the purpose to collect enough data for reliable estimates and model fits described above. On the other hand, monotonous tasks usually lead to disengagement and boredom, and consequent poor and variable task performance (Hawkins, Rae, Nesbitt, & Brown, 2013). Disengagement and boredom related performance issues might be more prevalent among pediatric groups and certain clinical disorders (i.e., Attention Deficit and Hyperactivity Disorder - ADHD) for instance due to associated attentional lapses. These task-engagement related issues might in turn contaminate the data and confound the analyses that aim to characterize putative differences in the decision process itself. A potential and contemporary way of overcoming these problems is embedding the task rules into games or adding game-like elements to the task.

Gamification is defined as “the use of game design elements in non-game contexts” (Deterding, Dixon, Khaled & Nacke, 2011, p.11), and such practice is increasingly applied in various domains (Ninaus, et al., 2015) including experimental psychology (Hawkins et al., 2013). For example, in their working memory training task, Ninaus et al. (2015) included game elements such as a progress bar, level marker, and a

theme. The group who completed the gamified version performed better than the group who participated in the original (non-gamified) version of the task. Moreover, both Shaw, Grayson, & Lewis (2005) and Prins, Dosis, Ponsioen, Ten Brink, and Van der Oord (2011) tested participants diagnosed with ADHD in gamified tasks. Prins et al. (2011) trained one group of ADHD patients for working memory in the game format and another group in a non-game format for three weeks. The game format group had both higher motivation and performed better than the control group. Similarly, Shaw et al. (2005) showed that ADHD patients performed better on a gamified continuous performance task (CPT II) than the original version.

The commonly-used 2AFC tasks (e.g., dot motion discrimination task) are also monotonous and it is difficult for participants to sustain task focus. In the same vein with prior efforts in the domain of working memory and attention, we developed a gamified 2AFC task that involved taking penalty shots in the context of soccer game. The advantages of our gamified task over already existing 2AFC tasks are that the task, its aim, and reward structure are familiar to the participants, and that the sequentially presented momentary evidence (which varies from one frame to the next due to noise) for two alternatives is not only observable to the participants but also to the experimenters during data analysis. Due to this last advantage, it is possible to reconstruct the evidence accumulation in each trial for an ideal observer.

Aims:

There were three primary aims of this work. The first aim was to test the basic form of the game with three difficulty levels to investigate their effect on decision outputs (i.e., accuracy and RT) as well as latent decision parameters. This test is essential for the validation of the task as a 2AFC paradigm within the framework of DDM.

The second aim was to observe differences in the task performance of the participants who ranked differently on various scales that measure Obsessive-Compulsive (OC) traits, trait anxiety, and perfectionism. Pertaining to non-clinical populations, decision-making in anxiety (White, Ratcliff, Vasey, & McKoon, 2010) and subclinical OCD (Erhan & Balci, 2016) have been previously studied within the framework of DDM, however perfectionism has not been studied in this context before. Perfectionism is a transdiagnostic trait that is argued to be a maintaining factor for OCD as well as a risk and maintaining factor for anxiety disorders. Perfectionism thwarts the treatment process, however when it is treated symptoms of clinical disorders lessen (Egan, Wade & Shafran, 2011). The close relationship of perfectionism with both

anxiety and OCD (e.g. Frost & DiBartolo, 2002) warrants its investigation within the same decision-theoretic framework.

The final aim of the current work is to provide an adaptable method (i.e., gamification of paradigms) to be used for a wide range of research areas in psychology, and to provide the developed game to other researchers, with easy documentation to facilitate the integration of a gamified task into their ongoing research. We believe that this will improve both the participants' experience during experimentation (an endpoint typically overlooked in experimental psychology) and the quality of data collected in the experiments.

Hypotheses:

We expected hierarchical drift diffusion model (HDDM; Wiecki, Sofer & Frank, 2013) to provide acceptable fit quality for the data gathered from the game. Primarily, we predicted error rates and RTs to increase and the drift rate to decrease with increasing task difficulty. We also predicted that there will be slowing and increased error rate accompanied by lower drift rates after errors compared to post-correct responses.

As for our second order predictions, we hypothesized people who ranked high on OC, anxiety, and perfectionism scales to have higher threshold settings than those who ranked lower on these scales (for these relations in subclinical OC traits, see Erhan & Balci, 2016). Since Banca et al. (2015) working with adult, and Erhan et al. (2017) working with pediatric OCD patients have shown that those diagnosed with OCD generally have lower drift rates than controls, we also predicted a residual decrease in drift rates from low to medium to high rankers on OC traits, perfectionism, and anxiety scales.

METHODS

Procedures

Task:

“Shoot” is a gamified two alternative forced choice task, where the participant is asked to take a penalty kick toward the left or right of a goal as fast and as accurately as possible for 20 minutes (**Figure 1**). During each shot, the goalkeeper moves laterally in the goal area and blocks one side of the goal more than the other. The player is asked to shoot towards the side that the keeper favors less in order to score. Immediate

feedback is provided after each kick and the total score is displayed at the top left of the screen throughout the task. The three difficulty levels (easy, moderate and hard) are interleaved and come up at a random order. The task was coded in the OpenSesame software (Mathôt, Schreij & Theeuwes, 2012) using the PyGame backend.

The goalkeeper's movement consisted of points sampled from a Gaussian distribution with a mean slightly to the left or right of the center (**Figure 2**). This deviation of the mean from the center results in the on average biased behavior of the goalkeeper. Thus, there are two hypotheses for the observer to test given the behavior of the goalkeeper: the goalkeeper's behavior comes from a normal distribution with the same variance and a mean either to the left ($x_{\text{center}} - \Delta x$) or to the right of the center ($x_{\text{center}} + \Delta x$), with the task becoming more difficult as the distance between the two distributions decreases. For this particular task, Δx is 80 pixels for the easy condition, 26 pixels for the moderate condition and 8 pixels for the difficult condition. The variance for all distributions is 80 pixels, and the total goal width is 320 pixels (**Figure 2**).

Scales:

Participants filled out 3 scales measuring individual differences in Obsessive-Compulsive (OC) traits (41 item Padua Inventory; Van Oppen, Hoekstra & Emmelkamp, 1995; validated in Turkish by Beşiroğlu et al., 2005), trait anxiety (STAI; State-Trait Anxiety Inventory trait form; Spielberger, Gorsuch & Lushene, 1970; validated in Turkish by Öner & Le Compte, 1985), and perfectionism (Frost Multidimensional Perfectionism Scale - FMPS; Frost, Marten, Lahart, & Rosenblate, 1990; validated in Turkish by Kağan, 2011). For the latter, maladaptive perfectionism scores were calculated using only the Concern About Mistakes and Doubts About Actions subscales of the FMPS as they are the two most relevant aspects for the transdiagnostic cognitive effects that we were interested in (see Egan, Wade & Shafran, 2011; Shafran & Mansell, 2001; Stöber, 1998).

Participants:

We tested 50 undergraduates from Koç University. Participants received course credit for their participation in the experiment. Participants played Shoot for 20 minutes and were instructed that being accurate and fast were equally important. After completing the task, they filled out three questionnaires (Padua, Trait anxiety form of STAI, and FMPS) to measure OC, anxiety, and perfectionism traits, respectively. We excluded 3 participants from our analyses; one due to premature termination of the task

(13 minutes instead of 20), and two due to random responding, spotted through irregularities in RT data (i.e. bimodal distribution and chance-level accuracy in easy and moderate levels). The experiment was approved by the Koç University Ethical Review Board and all participants signed an informed consent form.

Data analysis

Drift Diffusion Modeling:

Hierarchical Drift Diffusion Model (HDDM; Wiecki et al., 2013) was fit to response time distributions of correct and incorrect responses to estimate and compare latent decision variables such as drift rate, threshold, non-decision time, and starting point for different difficulty levels and in post-error compared to post-correct trials. We used two within-subjects designs; one to investigate the main effects of task difficulty and another to assess main effects of errors in previous trials (i.e. post-error effects) on drift rate, threshold, and non-decision times. We fit the model to each individual independently in order to avoid the loss of variance in the parameters that a hierarchical model would bring, as we were interested in the relationship of this variance with that in individual differences on scale scores. For the difficulty main effect analysis, we fit 7 different models with different parameter combinations in order to see which one was the best fit to our data. The simplest model (after the null model) had only drift rate that depended on task difficulty, whereas in the most complex model, task difficulty affected drift rate, threshold, non-decision time, and starting point. The post-error analysis only included the parameters from the best performing model from the difficulty analysis (namely; drift rate, threshold, and non-decision time).

For model fitting, we discarded trials with RTs faster than or equal to 100 ms (amounting to less than 1% of all trials) as they were too fast to have plausibly come from a decision process (i.e. premature responding), and thus not relevant for the HDDM analyses. All models had MCMC (Markov Chain Monte Carlo) chains of 5000 samples with the first 20 draws discarded as burn-in. We assessed model convergence using the traces, autocorrelations, and marginal posteriors of the sample chains. We performed model comparison using the DIC (Deviance Information Criterion), where the model with the lowest DIC for most of the individuals was picked as the best model, and the parameter outcomes from that model for every participant was used in the analyses that followed. We also simulated data with the model outcomes to perform parameter recovery. All variables in both models had satisfactory convergence, and parameters were successfully recovered from data simulated with the outcome of the model.

Mixed effects models:

We used mixed effects models to assess the effects of task difficulty, accuracy of previous trial and individual differences in scale scores on both behavioral and model outcomes. For behavioral outcomes, we investigated effects on median response times and accuracies. We preferred median as the central tendency measure as it is a more robust estimate of the typical values of characteristically skewed distributions of response times (Ratcliff, 1993). For model outcomes, we used the parameter estimates from drift diffusion model that was the best fit to the most individuals. For each outcome of interest, we compared four alternative linear mixed effects models, all with subjects as a random effect on the intercept; (1) a null model with no fixed effects, (2) a model with only task difficulty (or previous trial accuracy) as the fixed effect, (3) a model with task difficulty (or previous trial accuracy) and the scale score of interest as two fixed main effects, and (4) a model with an interaction and two main effects of task difficulty (or previous trial accuracy) and the scale score of interest. We picked the best out of these four nested models using Chi-square difference tests. We used the lme4 package (Bates, Mächler, Bolker & Walker, 2015) in R (R Core Team, 2018) for all mixed effects models.

RESULTS

Participants completed 506 trials (SD=102) on average in 20 minutes, with a minimum of 229 trials and a maximum of 755 trials. As expected, median RTs got slower as task difficulty increased from easy ($M = 657$ ms, $SD = 347$ ms), to moderate ($M = 877$ ms, $SD = 605$ ms), to hard ($M = 961$ ms, $SD = 779$ ms) conditions ($F(2, 94.1) = 16.244$, $p < 0.001$; $\beta_{\text{easy-mod}} = -0.206$, $SE = 0.052$, $p < 0.001$; $\beta_{\text{mod-hard}} = -0.081$, $SE = 0.051$, $p = 0.118$). Again as expected, accuracy levels dropped as task difficulty increased from easy ($M=90.7\%$, $SD=7.75\%$) to moderate ($M= 72.6\%$, $SD=7.97\%$) to hard ($M=58.2\%$, $SD=4.64\%$) levels ($F(2, 94.3) = 471.6$, $p < 0.001$; $\beta_{\text{easy-mod}} = 0.181$, $SE = 0.01$, $p < 0.001$; $\beta_{\text{mod-hard}} = 0.145$, $SE = 0.01$, $p < 0.001$). We observed no relationship of the behavioral outcomes with any of the scale scores.

Overall, participants responded more slowly after errors ($M = 904$ ms, $SD = 772$ ms) than after correct ($M = 795$ ms, $SD = 495$ ms) responses ($\beta_{\text{pc-pe}} = -0.113$, $SE = 0.0547$, $t(47) = , p < 0.044$). Moreover, accuracy was higher after correct responses ($M = 73.7\%$, $SD = 6.76\%$) than after errors ($M = 71.0\%$, $SD = 8.62\%$) ($\beta_{\text{pc-pe}} = 0.028$, $SE = 0.007$, $t(47) = 3.951$, $p < 0.001$). We did not observe any relationship between the scale scores and behavioral changes after errors.

Maladaptive perfectionism ($M = 32.6$, $SD = 9.05$, [12-53]), obsessive compulsive trait ($M = 55.7$, $SD = 25.8$, [7-126]) and trait anxiety ($M = 44.1$, $SD = 8.67$, [25-64]) scores were all positively correlated with each other. Perfectionism had positive linear relationships with both OC traits ($r=0.475$, $p<0.001$), and trait anxiety ($r=0.444$, $p=0.001$). There was also a positive linear relationship between OC traits and trait anxiety ($r=0.543$, $p<0.001$).

The best within-subject drift diffusion model (one where drift rate, threshold, and non-decision time values that varied according to difficulty levels) revealed that as task difficulty increased, drift rates decreased ($M_{v_easy}=1.34$, $M_{v_mod} = 0.51$, $M_{v_hard} = 0.16$; $F(2, 94) = 417.03$, $p < 0.001$; Intercept = 0.673, $SE = 0.027$, $\beta_{easy-mod} = 0.832$, $SE = 0.042$, $p < 0.001$; $\beta_{mod-hard} = 0.349$, $SE = 0.042$, $p < 0.001$), but threshold levels ($M_{a_easy} = 2.06$, $M_{a_mod} = 2.02$, $M_{a_hard} = 2.04$) and the non-decision times ($M_{t_easy} = 0.156$ s, $M_{t_mod} = 0.156$ s, $M_{t_hard} = 0.139$ s) remained stable across difficulty levels. Higher maladaptive perfectionism scores were associated with overall lower drift rates ($F(1,47) = 4.45$, $p=0.04$, $\beta = -0.0546$, $SE = 0.0259$) (**Figure 3**). We observed no further relationship between any other scale scores and any of the drift diffusion model parameters.

The within-subject model in which drift rate, threshold and non-decision time were allowed to vary only according to post-error and post-correct status, indicated that post-error trials had lower drift rates ($M_{v_pc} = 0.59$, $M_{v_pe} = 0.49$; $\beta_{pc-pe} = 0.106$, $SE = 0.019$, $t(47) = 5.517$, $p < 0.001$) (**Figure 4**) and higher thresholds ($M_{a_pc} = 1.95$, $M_{a_pe} = 2.04$; $\beta_{pc-pe} = -0.087$, $SE = 0.032$, $t(47) = -2.68$, $p = 0.01$) than post-correct trials, but the non-decision time ($M_{t_pe} = 0.142$, $M_{t_pc}=0.156$) remained the same. We observed the main effect of maladaptive perfectionism scores on drift rates (but not the other parameters) in this models as well ($F(1,47) = 5.15$, $p=0.028$, $\beta = -0.0458$, $SE = 0.0202$). We did not observe any change in post-error behavior in relation to individual differences in any of the scale scores.

DISCUSSION

We developed a gamified 2AFC task in which participants made repeated decisions based on observed evidence (i.e., movements of the goalkeeper) about which side of the goal to shoot at for a score. We manipulated the task difficulty by parameterizing the distribution that guided the movements of goalkeeper from one frame to the next. The aim of this study was threefold: 1) to observe whether behavioral outputs (e.g. RT and accuracy) as well as latent decision variables estimated from model (HDDM) fits behaved in predicted directions and thereby validated “Shoot” as a

2AFC task; 2) to investigate how anxiety, perfectionism and OC traits are related to DDM variables; 3) to provide an easy to use gamified task for researchers to integrate into decision-making studies.

Regarding the first facet of the study, we expected HDDM to provide good fits to the data, and predicted that response times would increase and accuracy and drift rates would decrease with increasing task difficulty (e.g., see Balci et al., 2011) and after incorrect responses. Regarding the second facet of the study and based on our previous results reported in Erhan and Balci (2016), we expected those who ranked higher on OC, anxiety, and perfectionism scales to have higher threshold settings than those who ranked lower on these scales. Since Banca et al. (2015) and Erhan et al. (2017) generally found a decrement in drift rates of OCD patients, we also expected those who scored high on these scales to have lower drift rates. Our prediction and intention regarding the third facet of the study can only be tested over the next years.

Our predictions regarding the basic behavioral and model outcomes were confirmed. Specifically, response times and error rates increased whereas drift rates decreased with increasing task difficulty. We did not predict different threshold settings for different task difficulties since difficulty levels were randomly assigned for each trial instead of being presented in separate blocks (Bogacz, Brown, Moehlis, Holmes & Cohen, 2006). In line with this theory-driven rationale, thresholds remained stable across different difficulties. Another typical effect observed in 2AFC tasks is change in behavior after incorrect responses, as participants typically slow down after errors (i.e. post-error slowing). In line with our predictions regarding post-error behavior, participants are slower, more error-prone, more cautious and less efficient in evidence accumulation in trials that follow an erroneous response compared to trials that follow a correct response. “Shoot” can therefore elicit typical characteristics of 2AFC tasks as it pertains to both behavioral outcomes and drift diffusion model parameters.

Our predictions regarding the relationship between threshold settings and scores on the scales were not confirmed, but our predictions regarding the relationship between scale scores and drift rates were partially confirmed. We observed that individuals with higher maladaptive perfectionism scores tend to process information less efficiently compared to those who score lower on this scale. We did not detect any other relationship between scale scores and latent decision variables, in contrast to our literature-guided expectations, especially regarding OC traits (Erhan & Balci, 2016). However, individual differences in perfectionism have not been studied in this decision model context before, and considering the transdiagnostic nature of this trait, our

finding could be considered as congruent with the results of Banca et al. (2015; see also Erhan et al., 2017) and Metin et al. (2013) where drift rates were observed to be lower in both OCD and ADHD groups compared to healthy controls.

Previously, based on the differential results gathered with subclinical OC and clinical OCD, Erhan and Balcı (2016) had argued that changes in drift rates might be a diagnostic signature of clinical OCD. The lack of a relationship between OC traits and drift rates in this subclinical sample is thus in line with these findings. However, the same line of research led to an expectation of a relationship between OC traits and threshold settings, which we did not detect with the current paradigm. This may have resulted from the frequent change in difficulty from one trial to the next, which requires a different decision policy than when facing a constant signal-to-noise ratio throughout several consequent trials. This experimental design, rather than the task itself, might have thwarted differences in threshold settings between participants of various ranks on the scales. Further studies are needed to elucidate the factors that might have led to differential results between different tasks.

Importantly, maladaptive perfectionism, argued to be associated with both OC and anxiety traits (Frost & DiBartolo, 2002) followed a pattern that we would expect from a clinical OCD sample; as perfectionism scores increased, drift rates decreased. Interestingly, individual differences in this trait were related to drift rates in a task that presumably minimized the between-subject variability in drift rates by minimizing differences in perceptual processing of sensory stimulus (due to clear sequential indication of the momentary evidence at each frame). Thus, the observed between-group differences are more likely due to differences in evidence integration ability itself. For instance, each piece of information might be weighted less in participants who score high on perfectionism. An alternative explanation relates to the width of the window over which information is integrated by participants, or the decrement in the contribution of previous bits of evidence to the current estimates of the state of the world; this window might be shorter or the contribution of the previous evidence might be lower for high scorers due to factors such as working memory deficits (e.g. Desnoyers & Arpin-Cribbie, 2013). However, we do not see any relationship between drift rate and OC and anxiety traits despite both traits also being associated with deficits in working memory (de Vries et al., 2014; Eysenck, Derakshan, Santos & Calvo, 2007), so this potential explanation warrants some caution.

An important advantage of the presented game is the ability to record the momentary state of evidence as observed by the participants, which allows to

reconstruct the exact trajectory of the belief state of an ideal observer. This perfectly tractable information within each trial might prove useful in reducing the number of parameters in the models developed/fit to explain the generative processes that underlie two alternative forced choice behavior.

We believe that this work provides a good exemplar to other researchers for participant-experience-centered experiment design to improve task engagement, experience of the participants, and the quality of data. This becomes particularly beneficial in studies with pediatric and clinical samples. We find that conventional tasks with novel stimulus (such as random dot motion discrimination) increase the risks of not-understanding task rules, require longer practice to familiarize participants with stimulus and task rules, and lead to boredom during testing. One of these factors or their combination poses difficulties for gathering high quality behavioral data and leads to the contamination of task performance due to factors not directly relevant for research questions. Secondly, we believe that improving the quality of participant experience is a factor that should be observed during the development of experimental tasks for ethical reasons and to minimize attrition in studies that require repeated testing. Finally, gamification of conventional tasks paves the way to large-scale and high-throughput testing outside the lab setting for instance through mobile devices.

Author Notes

First three authors contributed equally to the study and the preparation of the manuscript. KK, CK, and FB designed the task, KK coded the game, CK and ET conducted the experiments and analyzed the data, all authors wrote the manuscript. Experiment and analysis code is available upon request. Authors report no conflicts of interest.

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FIGURES

Figure 1. A screenshot from the task. The goalkeeper continuously moves laterally. The player's task is to decide shooting the ball to the left or right of the goalkeeper, towards the side the goalkeeper favors less. Note that the ball is placed slightly to the left of center -- this was the case in all trials. We included the starting point parameter in the HDDM analyses to check for the potential effects of ball placement on bias, but the DIC values did not improve enough to justify the inclusion.

Figure 2. The keeper movement distributions for 3 different difficulty levels. The green distributions represent the easy level, where the keeper moves by sampling from a distribution with a mean of 80 pixels to the right or to the left of the goal center. For the moderate (blue) and hard (red) levels, the means of the distributions are 26 and 8 pixels away from the central point, respectively. For all distributions, the variance is 80 pixels.

Figure 3. The effects of difficulty and individual differences in maladaptive perfectionism scores on drift rate. The lines are the predicted drift rates from the best fitting linear mixed effects model, while the dots are the ‘observed’ drift rates from the best fitting drift diffusion model. The faded gray lines show the predictions for each participant, varying due to the random effect of each participant on the intercept. The bold lines show the predicted drift rate, varying due to the fixed effects of difficulty and perfectionism scores. The blue end of the spectrum stands for low scores while the red end is for the high scores.

Figure 4. The effects of accuracy in the previous trial and individual differences in maladaptive perfectionism scores on drift rate. The lines are the predicted drift rates from the best fitting linear mixed effects model, while the dots are the ‘observed’ drift rates from the best fitting drift diffusion model. The faded gray lines show the predictions for each participant, varying due to the random effect of each participant on the intercept. The bold lines show the predicted drift rate, varying due to the fixed effects of the previous trial and perfectionism scores. The blue end of the spectrum stands for low scores while the red end is for the high scores.