Differential Sensitivity of Cognitive Flexibility Measures in Anorexia Nervosa: A

Comparative Evaluation of the Probabilistic Reversal Learning Task, Wisconsin Card

Sorting Test, and Task Switching

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16   Abstract

17   One or two sentences providing a **basic introduction** to the field, comprehensible to a

18   scientist in any discipline. Two to three sentences of **more detailed background**,

19   comprehensible to scientists in related disciplines. One sentence clearly stating the **general**

20   **problem** being addressed by this particular study. One sentence summarizing the main

21   result (with the words "**here we show**" or their equivalent). Two or three sentences

22   explaining what the **main result** reveals in direct comparison to what was thought to be

23   the case previously, or how the main result adds to previous knowledge. One or two

24   sentences to put the results into a more **general context**. Two or three sentences to provide

25   a **broader perspective**, readily comprehensible to a scientist in any discipline.

26   *Keywords:* keywords

27   Word count: X

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Methods

We report how we determined our sample size, all data exclusions (if any), all

manipulations, and all measures in the study.

Participants

Material

Procedure

Data analysis

Data Analysis.

Computational Modeling.   In this study, we employed three computational models

to analyze the data from the three behavioral tasks: the Wisconsin Card Sorting Task

(WCST), the Probabilistic Reversal Learning (PRL) task, and the Task Switching (TS) task.

Each model was chosen to capture the specific cognitive processes underlying performance in

these tasks.

Task Switching: Drift Diffusion Model (DDM).   For the Task Switching data,

we used the Drift Diffusion Model (DDM) to analyze participants' performance. The DDM

is a widely used cognitive model that describes the decision-making process as a stochastic

accumulation of evidence over time until a decision threshold is reached. This model is

particularly suited for tasks requiring speeded binary decisions, such as the Task Switching

task, where participants must quickly decide between continuing with a previous task or

switching to a new one.

For each participant, we computed three key parameters of the DDM separately for

52 "repeat" and "switch" trials:

53 1. **Drift Rate (v)**: This parameter represents the average rate of evidence accumulation.
54   A higher drift rate indicates faster and more accurate decision-making, reflecting better
55   task performance.

56 2. **Boundary Separation (a)**: This parameter reflects the amount of evidence required
57   to make a decision. Larger values of boundary separation indicate a more cautious
58   decision-making strategy, where more evidence is needed before committing to a choice.

59 3. **Non-decision Time (t)**: This parameter accounts for the time taken by processes
60   other than decision-making, such as sensory encoding and motor execution. It is the
61   time elapsed before the decision process begins.

62 By analyzing the DDM parameters separately for "repeat" and "switch" trials, we can
63 gain insights into how cognitive control and flexibility are modulated during task switching.
64 Specifically, differences in drift rates between "repeat" and "switch" trials can reveal the
65 efficiency of cognitive processes involved in maintaining or shifting task sets, while variations
66 in boundary separation and non-decision time can provide information about decision
67 strategies and preparatory processes.

68 ***Probabilistic Reversal Learning: The Reinforcement Learning Drift***
69 ***Diffusion Model.***

70 **Data Analysis.**

71 ***Computational Modeling.*** In this study, we employed three computational models
72 to analyze the data from the three behavioral tasks: the Wisconsin Card Sorting Task
73 (WCST), the Probabilistic Reversal Learning (PRL) task, and the Task Switching (TS) task.
74 Each model was chosen to capture the specific cognitive processes underlying performance in
75 these tasks.

76 ***Probabilistic Reversal Learning: Reinforcement Learning Drift Diffusion***

77 ***Model (RLDDM).*** For the Probabilistic Reversal Learning (PRL) task, we utilized the

78 Reinforcement Learning Drift Diffusion Model (RLDDM) as described by Pedersen and

79 Frank (2020). This model integrates elements of both reinforcement learning and the drift

80 diffusion model to provide a comprehensive account of decision-making processes that

81 involve both learning from probabilistic outcomes and making decisions based on

82 accumulated evidence.

83 The RLDDM captures two key aspects of behavior in the PRL task:

84 1. **Reinforcement Learning Component.** The model uses the delta learning rule to

85 update the expected values (Q-values) of different options based on reward feedback.

86 This rule is expressed as:

$$Q_{o,i} = Q_{o,i-1} + \alpha(\text{Reward}_{o,i-1} - Q_{o,i-1}),$$

87 where $Q_{o,i}$ is the expected value of option o on trial i, α is the learning rate, and

88 $\text{Reward}_{o,i-1}$ is the reward received for option o on trial $i-1$. The learning rate α determines

89 the speed at which the model updates its expectations based on new information.

90 2. **Drift Diffusion Component.** The decision-making process is modeled as a drift

91 diffusion process where evidence accumulates over time until a decision threshold is

92 reached. The drift rate (v) in the RLDDM is influenced by the difference in Q-values

93 between the options, scaled by a parameter similar to the inverse temperature

94 parameter in the softmax function used in traditional RL models. The drift rate for

95 trial i is given by:

$$v_i = (Q_{\text{upper},i} - Q_{\text{lower},i}) \times v,$$

96 where $Q_{\text{upper},i}$ and $Q_{\text{lower},i}$ are the Q-values for the options associated with the upper

97 and lower decision thresholds, respectively, and v is a scaling parameter that controls the

98 exploration-exploitation balance. Additionally, the RLDDM includes parameters for

99 boundary separation (a) and non-decision time (t).

100 By integrating reinforcement learning and decision-making processes, the RLDDM

101 provides a detailed and nuanced understanding of how participants learn from probabilistic

102 outcomes and make decisions based on accumulated evidence. This model is particularly

103 suited for capturing the complexities of cognitive rigidity and flexibility in anorexic patients

104 compared to healthy controls.

105 ***Wisconsin Card Sorting Task: Reinforcement Learning Models.*** For the

106 Wisconsin Card Sorting Task (WCST), we followed the model selection procedure outlined

107 by Steinke, Lange, and Kopp (2020). This involved computing the Widely Applicable

108 Information Criterion (WAIC) for all the Reinforcement Learning (RL)-based models

109 considered by Steinke et al., and selecting the best model based on the lowest WAIC value.

110 The WAIC provides a measure of model fit while penalizing model complexity, thus

111 balancing goodness-of-fit with model parsimony. We compared several models, including

112 pure Model-Based (MB) RL, pure Model-Free (MF) RL, and parallel MB-MF RL models

113 (Steinke et al., 2020). Consistent with their findings, the weighted Parallel Reinforcement

114 Learning (wP-RL) model emerged as the best-fitting model for our data.

115 The wP-RL model integrates both MB and MF reinforcement learning processes to

116 explain card sorting performance. The model assumes that participants use feedback to

117 update their expectations about categories (model-based) and responses (model-free) in

118 parallel, which are then linearly combined to determine behavior.

119 1. **Model-Based Learning**:

120 - The MB component involves updating feedback expectations for different sorting

121 categories. This is achieved using a delta-learning rule, where the prediction error

122 (the difference between expected and received feedback) adjusts the expected

123 value of the selected category.

124   • Learning rates (α_{MB}^{+} for positive feedback and α_{MB}^{-} for negative feedback)

125   determine the extent of these adjustments.

126   • An inertia parameter (γ_{MB}) accounts for the persistence of feedback expectations

127   across trials.

128   2. **Model-Free Learning**:

129   • The MF component updates feedback expectations directly based on the executed

130   response, independent of the abstract sorting category.

131   • Similar to the MB component, it uses separate learning rates (α_{MF}^{+} for positive

132   feedback and α_{MF}^{-} for negative feedback) and an inertia parameter (γ_{MF}).

133   3. **Integration and Response Selection**:

134   • The integrated feedback expectation for a response ($Q_{sum}(t)$) is a weighted sum of

135   the MB and MF expectations. A weighting parameter (w) quantifies the relative

136   influence of the MB and MF components.

137   • The probability of selecting a response is determined using a softmax function

138   applied to the integrated feedback expectations, modulated by a temperature

139   parameter (τ) that controls the randomness of choices.

140   Steinke et al. argued that RL-based models, particularly those integrating both MB

141 and MF processes, provide a more comprehensive account of WCST performance compared

142 to traditional models. This is because the RL framework can capture the dynamic updating

143 of expectations based on feedback, which is crucial for tasks requiring cognitive flexibility

144 like the WCST.

145   The superiority of the wP-RL model, both in our study and in Steinke et al. (2020)

146 research, underscores the importance of considering multiple levels of learning (both

147 categorical and response-based) in understanding cognitive processes. The wP-RL model's

148 ability to simulate perseveration errors and their modulation by response demands further

149 supports its validity as a robust computational framework for analyzing cognitive rigidity in

150 anorexic patients.

151   ***Estimation Method for Computational Models.*** To estimate the parameters of

152 the three computational models used in this study, we employed a hierarchical Bayesian

153 framework implemented in the hDDM Python package. This method allows for the

154 estimation of individual-level parameters while accounting for between-subject variability

155 through a hierarchical structure, enhancing parameter identifiability and robustness,

156 especially when dealing with noisy behavioral data.

157   The hDDM package utilizes Markov Chain Monte Carlo (MCMC) sampling to

158 generate posterior distributions for the model parameters and was employed for estimating

159 the parameters of the DDM and RLDDM models. We used a custom Stan model for

160 estimating the parameters of the WCST models (Steinke et al., 2020).

161   This probabilistic approach provides several advantages, including the ability to

162 incorporate prior knowledge, improve parameter estimation accuracy, and handle the

163 variability in participants' data more effectively. The MCMC sampling enables us to quantify

164 the uncertainty in our parameter estimates and make inferences about the cognitive

165 processes underlying task performance.

Results

167 **Results.**

168   ***Behavioral Indices.*** The primary objective of this study was to evaluate the

169 efficacy of three behavioral tasks—Wisconsin Card Sorting Task (WCST), Probabilistic

170 Reversal Learning (PRL) task, and Task Switching (TS) task—in measuring cognitive

171 rigidity in anorexic (AN) patients compared to healthy controls. Behavioral indices were

172 computed for each task and subsequently analyzed using logistic regression models to

173 differentiate between the two groups.

174   The Area Under the Curve (AUC) values, which represent the discriminatory power of

each task, are presented in Table 1. The WCST, commonly used in cognitive rigidity studies,

yielded an AUC of 0.645 (95% CI: 0.546, 0.709). In comparison, the PRL task, which

measures reinforcement learning, achieved a higher AUC of 0.759 (95% CI: 0.728, 0.771).

The TS task, measuring pure task-switching abilities, showed an AUC of 0.770 (95% CI:

0.745, 0.778).

Comparison of Behavioral Indices. Comparative analysis of the behavioral

indices between the tasks revealed significant differences. The PRL task demonstrated a

significantly higher AUC compared to the WCST (AUC difference = 0.114, 95% CI: 0.042,

0.216) and the TS task (AUC difference = -0.0111, 95% CI: -0.044, 0.0183). The difference

in AUC between the TS task and the WCST was also significant (AUC difference = 0.125,

95% CI: 0.0575, 0.225).

Computational Modeling. In addition to behavioral indices, computational

models were employed to derive more nuanced predictors of task performance. These models

were used to further assess the discriminative ability of each task.

The AUC for the PRL task based on computational modeling was 0.805 (95% CI:

0.769, 0.827), higher than the WCST (AUC = 0.717, 95% CI: 0.651, 0.763) and the TS task

(AUC = 0.752, 95% CI: 0.713, 0.774). The differences in AUC values based on

computational modeling were as follows: PRL vs. WCST (AUC difference = 0.0879, 95% CI:

0.0294, 0.158), PRL vs. TS (AUC difference = 0.0529, 95% CI: 0.00988, 0.0984), and TS

vs. WCST (AUC difference = 0.0350, 95% CI: -0.0252, 0.106).

Behavioral Indices vs. Computational Modeling. Comparing the behavioral

indices with computational modeling results for each task, the PRL task showed a moderate

difference (AUC difference = 0.0460, 95% CI: 0.00612, 0.0844), indicating some additional

discriminatory power from the computational model. For the TS task, the difference was

-0.0179 (95% CI: -0.0592, 0.0147), and for the WCST, the difference was 0.0723 (95% CI:

-0.0253, 0.185).

Summary. Overall, the PRL task demonstrated superior discriminative ability compared to both the WCST and TS tasks, suggesting it provides a more accurate measure of cognitive rigidity in AN patients. The computational modeling reinforced these findings, although the additional predictive power over behavioral indices alone was moderate. These results highlight the importance of selecting appropriate tasks and methodologies for assessing cognitive rigidity in clinical populations.

Table 1. AUC values for behavioral tasks and their comparisons

Table 2. AUC differences for task comparisons

These findings underscore the utility of the PRL task in clinical assessments of cognitive rigidity, with implications for both research and clinical practice in anorexia nervosa. These results suggest that the PRL task, particularly when analyzed using computational modeling parameters, provides the best discrimination between AN patients and healthy controls. This finding supports the notion that associative learning processes, as measured by the PRL task, may be a more sensitive marker of cognitive rigidity in AN compared to task switching abilities or the combined measure provided by the WCST.

Discussion

References

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Task	AUC	95% CI
WCST	0.717	0.651, 0.763
PRL	0.805	0.769, 0.827
TS	0.752	0.713, 0.774

Comparison	AUC Difference	95% CI
PRL vs. WCST (Behavioral)	0.114	0.042, 0.216
PRL vs. TS (Behavioral)	-0.0111	-0.044, 0.0183
TS vs. WCST (Behavioral)	0.125	0.0575, 0.225
PRL vs. WCST (Computational)	0.0879	0.0294, 0.158
PRL vs. TS (Computational)	0.0529	0.00988, 0.0984
TS vs. WCST (Computational)	0.0350	-0.0252, 0.106