Efficient assessment of Emotional Bias using Item Response Theory and Decision Tree Computerised Adaptive Testing.

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Background

Emotional processing bias has been proposed to be a core feature of mood disorders, particularly depression, and has been proposed to be both responsive to antidepressant treatment and a predictor of long-term outcomes. Here we describe the application of Item Response Theory (IRT) and Decision Regression Trees (DRT) to model an adaptive and abbreviated version of the CANTAB Emotional Bias Task (EBT), and the implementation of this approach to produce a brief, adaptive version of the EBT task, suitable for high-frequency use.

Methods

Emotional Bias Task (EBT)

Participants are briefly presented with 45 facial expressions from a 15-step morph sequence from happy to sad, followed by a masking image, and are asked judge which emotion they saw (Figure 1). The bias point indicates when a participant is equally likely to endorse either emotion.

Item Response (IRT) Analysis of EBT

- 737 adult (>18 yrs) were recruited through Prolific (https://www.prolific.ac/) platform for web-based studies. Participant characteristics for the normative sample are shown in Table 1.
- We modelled two IRT parameters for each emotion morph (difficulty and discrimination), predicting participant latent emotional bias (Theta).

Decision Regression Tree (DRT) construction

- The IRT model above was input to the mirtCAT package to generate a set of plausible synthetic happy / sad responses which correspond to particular Theta values, based on the item IRT parameters. Data from 10,000 synthetic participants were generated, following a uniform distribution of Theta between -5 and 5.
- The synthetic data were used to generate a DRT using the Rpart package. Binary happy / sad response at each trial predict the continuous theta outcome, thus modelling the underlying emotional bias trait rather than conventional bias point. Each node represents a choice of stimulus to present at that trial, dependent on prior responses, and each leaf represents final a predicted Theta. Therefore, each participant follows one of many possible paths through a deterministic, adaptive sequence of trials. The regression tree was specified to have a minimum of five observations at each leaf node and a maximum depth of 30. This produces a large tree, with granular resolution of theta at the leaf nodes, at the expense of potential overfitting.

Adaptive EBT validation

- Modelled performance on abbreviated adaptive version of EBT was compared against the full-length scores in a n = 100 sample of synthetic data, generated as above, following a normal distribution of Theta with mean 0 and an SD of 2.
- A software implementation of the adaptive EBT (EBT-A) was built, which presented stimuli according to the DRT rules. The full length EBT and EBT-A were deployed onto the Prolific testing platform for web basted studies.
- Participants were presented with both versions in a counterbalanced order, with half taking the abbreviated version first and half the full-length version first.
- Data from 73 participants aged 18-65 is reported. Participant characteristics are shown in Table 2.

Table 1: Normative data participant characteristics

Age (Years)	36.88 (11.84)
Sex (% Male)	43
Max. level of education completed (%)	
Left formal education at or before 16	9.65
Left formal education age 17-18	23.76
Undergraduate degree or equivalent	47.40
Masters degree or Higher	19.31

Figure 1: Examples of the Emotional Bias Stimuli. Each face is a morph of multiple individuals and a mixture of emotions from happy to sad in different proportions.

Results

IRT Analysis

- Distribution of Emotional Bias Score in the normative sample is shown in Figure 2. The neutral point is at an emotion intensity of 7.5. In the normative sample there is a slight positive emotional bias.
- Results of the IRT analysis are shown in Figure 3. Figure 3a shows the distribution of the IRT difficulty parameter, and Figure 3b the distribution of the discrimination parameter by morph intensity.
- The difficulty parameter determines the way in which items behave along the underlying bias scale (Theta). It is the point of median probability, i.e., the Theta at which 50% of respondents endorse face morph as "Happy".
- Extreme morphs are endorsed by those with very high or low Theta, whereas mid-point morphs were found to have a difficulty parameter close to 0, indicating that they are equally likely to be reported to be happy as sad (Figure 3a).
- The discrimination parameter (Figure 3b) determines the rate at which the probability of endorsing an item as happy changes given Theta levels. Higher values indicate that response to an item is more able to discriminate between Theta levels. Items of maximum discrimination were located towards the mid-point of the scale (intensity 6-10), which represent the most ambiguous facial expression.

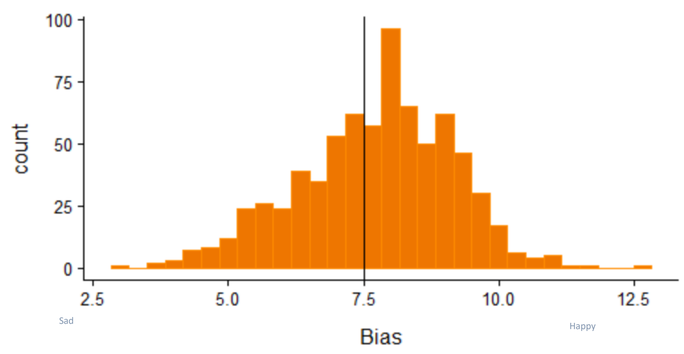

Figure 2: Distribution of Emotional Bias score in the normative sample.

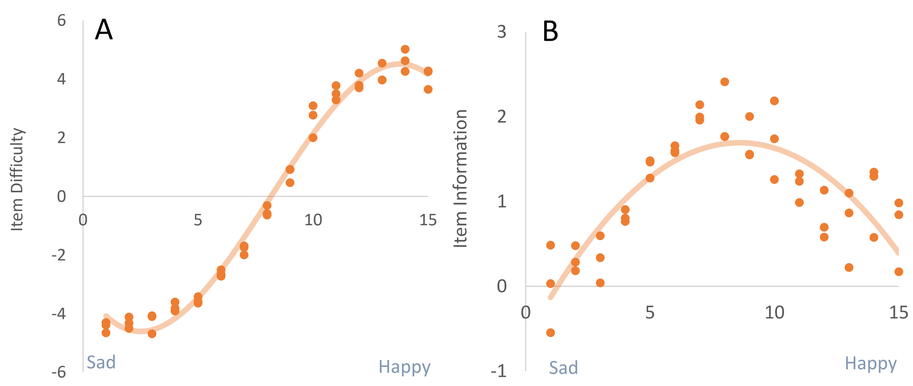

Figure 3: Item Response Characteristics for each emotion intensity morph. As each intensity was presented three times to each participant, three estimates are generated.

Decision Regression Trees (DRT)

- A DRT was fitted to the simulated data to predict Emotional Bias Theta values, and construct rules for an abbreviated decision tree based EBT.
- The tree had 1235 nodes, however the average depth of the tree, and therefore the number of trials for each participant would be presented is 10.27 (range 6 – 19).
- Log Variable importance is shown in Figure 4. Consistent with the results of the IRT analysis, the DRT model made most use of responses to morphs at intensities between 5 and 11 to differentiate levels of Theta, although morphs at the more extreme ends were occasionally presented.

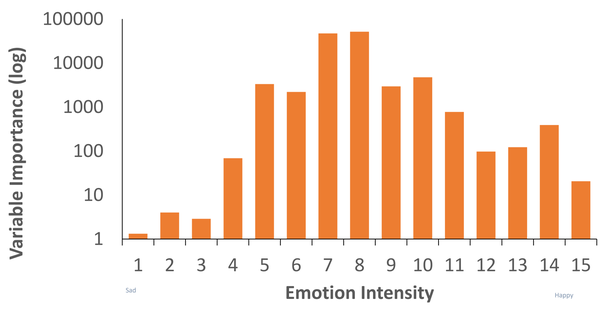

Figure 4: Mean variable importance by emotion intensity.

Validation of Abbreviated EBT (EBT-A)

- Initial validation was performed by comparing Theta produced by simulated performance on the DRT against pre-specified Theta (Figure 5a). A correlation of r = .95 (p < 0.001) was observed.

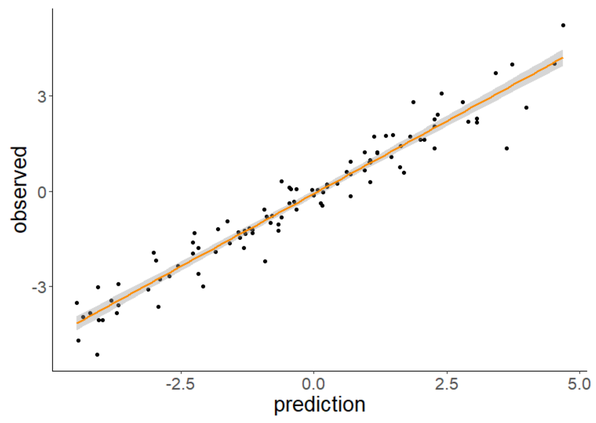

Figure 5: Scatter plot of the correlation between predicted Theta derived from the DRT and observed synthetic values.

- The participant characteristics for the validation sample are shown in Table 2, below. These participants completed both EBT-A and EBT.
- The mean number of trials administered in the EBT-A was 9.6 (min = 7; max = 15), compared to 45 in the full length version.
- We observed a correlation of r=.46 (p<0.001) between full length EBT bias point, and the estimate derived from the EBT-A.

Table 2: Validation data participant characteristics

Characteristics	Values
Age (years)	26.8 (8.63)
Sex (% Male)	41 %
Max. level of education completed (%)	
Middle School/Junior High School	63 %
High School	21 %
Higher Education	15 %
Postgraduate Education	1 %

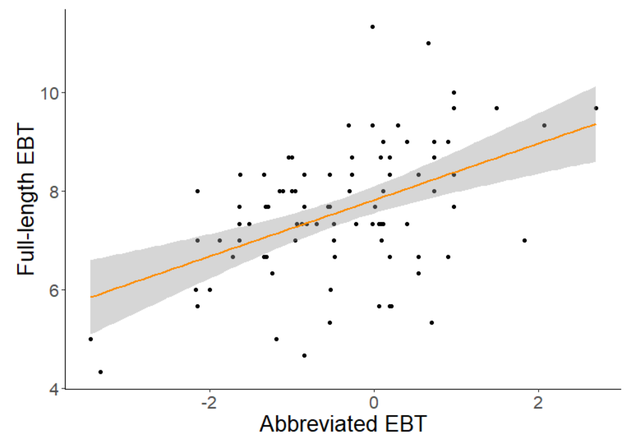

Figure 6 Scatter plot of the correlation between bias scores from the abbreviated and full-length versions of the EBT.

Conclusions

We have used IRT analysis of the CANTAB EBT in a normative sample to derive a DRT-based adaptive version of the task. This abbreviated, adaptive form is considerably briefer than current version, which may have utility in high-frequency testing scenarios. Future work will examine performance in the context of repeated administrations in patients with mood disorders.

Disclosures

This work was funded by Cambridge Cognition who commercialise the CANTAB Emotional Bias Test. The authors are employees of Cambridge Cognition. One or more authors report potential conflicts which are described in the program.

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