It is important to keep in mind that performance in the this task can be affected by factors outside of the ability to discriminate safe and threatening faces. For example individuals might differ in how cautiously they respond (i.e., their speed/accuracy tradeoff), which can affect their response speed, accuracy, and likelihood of successful inhibition on nogo trials. Further, myriad studies have shown that factors like response caution vary as a function of age, with older adults typically being more cautious than younger adults (e.g., Starns & Ratcliff, 2011). To account for factors like response caution, a drift-diffusion model (DDM, Ratcliff, 1978) of simple decisions was fitted to the behavioral data. The model takes accuracy and response time data to estimate values for different components of the decision process. For the present purposes, the DDM was fit to each individual’s data to extract values for response caution, response bias, stimulus discriminability, and motor execution time (how long it takes to press the button). There are two primary advantages to this type of analysis. First, each of the different decision components can be compared to see if they vary with age. Second, the DDM controls for the effects of the other decision components when estimating the construct of main interest, how the ability to inhibit responses to safe and threatening faces. This type of model-based approach has been successfully applied to examine group differences in developmental studies (Ratcliff, Love, Thompson, & Opfer, 2012), aging studies (Starns & Ratcliff, 2011) and psychopathology studies (White, Ratcliff, Vasey, & McKoon, 2010a,b).

Method

*Drift Diffusion Model*

A DDM (Ratcliff, 1978; Ratcliff & Smith, 2004) was fit to each participant’s behavioral data to extract components of psychological processing. The model assumes that noisy evidence is accumulated over time until a boundary is reached, signaling a commitment to that response (Figure X). The decision time is calculated as the time taken to reach a boundary, and the overall response time is equal to the decision time plus a value of nondecision time that accounts for the duration of other processes like encoding and motor execution. Previous work shows that the DDM can successfully account for no-go data by assuming that there is an implicit boundary representing the no go option, meaning the individual commits to withhold the response once that boundary is reached (Gomez, Ratcliff, & Perea, 2007).

The primary components of the model are the boundary separation, nondecision time, starting point, and drift rate. The boundary separation provides an index of response caution (the speed/accuracy tradeoff); wide boundaries indicate a cautious response style that prefers accuracy over speed. The starting point, *z*, provides an index of response bias. In the no go task, people are generally biased toward the go response because those trials are much more probable than no go trials (Gomez et al., 2007). This is reflected by a shift in the starting point toward the go boundary, meaning less evidence is required for that response. The nondecision time (time for encoding and response, *Ter*) provides an index of the duration of nondecision processes, including encoding of the stimulus and execution of the response. Finally the drift rate (*v*) provides an index of evidence from the presented stimulus; higher absolute values of drift rate indicate strong evidence and lead to fast and accurate responses. In this present task drift rate indexes how effectively the threat and safe faces can be mapped onto the correct responses. Four drift rates were calculated based on the stimulus conditions; safe-face go trials, safe-face no go trials, threat-face go trials, and threat-face no go trials. Following convention, drift rates for go trials are positive and drift rates for no go trials are negative.

(Place Figure x about here)

The DDM was designed to account for the full observable data from all trials. This includes accuracy and the distribution of RTs for go trials, as well as the percentage of commission errors and their RTs on no go trials. The model was fit to each participant’s data separately for the two sessions, estimating for each session a value of response caution, drift rate for safe faces, drift rate for threat faces, response bias, and nondecision time. A parameter for across-trial variability in starting point was added to capture trial-by-trial fluctuations in response bias, allowing the model to account for extremely fast responses (i.e., guesses). Although this parameter helps the model fit the data, it is not generally used for inference and thus is not discussed further. The fitting process used the χ2 minimization technique (Ratcliff & Tuerlinckx, 2002) based on the quantiles of the RT distribution. For correct go responses, the standard quantiles of the RT distribution (.1, .3, .5, .7, .9) were used to compare against the predicted data from the model. Since there were so few commission errors, only the median quantile (.5) was used for commission responses. These RT quantiles were used with the proportion of each trial type (correct or omission) to provide the χ2 fit index, which was minimized by a SIMPLEX routine.

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Figure X. A schematic of the DDM. After the stimulus is encoded, noisy evidence is sampled over time until one of the boundaries is reached (see text for details).

Figure X2. Fit quality from the DDM. Predicted values from the best fitting DDM parameters are plotted against the observed values for the proportion of correct go responses (upper left), the RT quantiles for go responses (lower), and the median RT for commission errors (upper right). Each point represents a participant. The correspondence between observed and predicted values shows that the model captured the data well.