

Individual differences in emotion word processing: A diffusion model analysis

Christina J. Mueller^{1,2} · Lars Kuchinke^{1,2}

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Abstract The exploratory study investigated individual differences in implicit processing of emotional words in a lexical decision task. A processing advantage for positive words was observed, and differences between happy and fear-related words in response times were predicted by individual differences in specific variables of emotion processing: Whereas more pronounced goal-directed behavior was related to a specific slowdown in processing of fear-related words, the rate of spontaneous eye blinks (indexing brain dopamine levels) was associated with a processing advantage of happy words. Estimating diffusion model parameters revealed that the drift rate (rate of information accumulation) captures unique variance of processing differences between happy and fear-related words, with highest drift rates observed for happy words. Overall emotion recognition ability predicted individual differences in drift rates between happy and fear-related words. The findings emphasize that a significant amount of variance in emotion processing is explained by individual differences in behavioral data.

Keywords Individual differences · Emotion processing · Lexical decision task · Diffusion model · Dopamine

✉ Christina J. Mueller
christina.mueller-g4m@rub.de

✉ Lars Kuchinke
Lars.Kuchinke@rub.de

¹ Experimental Psychology & Methods, Ruhr Universität Bochum, Universitätsstraße 150, 44780 Bochum, Germany

² International Psychoanalytic University Berlin, Berlin, Germany

Even though individuals process emotional stimuli differently (Hamann & Canli, 2004), most studies on emotion processing focus on average values across entire samples in order to observe effects of experimental manipulations that can be generalized across the population. However, as Hamann and Canli point out, taking into account individual differences might be one way to overcome statistically nonsignificant group averages in emotion research. Similarly, Eugène et al. (2003) suggest that individual differences can explain inconsistencies on neural activation patterns of basic emotion processing that are evident in the corresponding functional imaging literature. Group averages are limited in their informative value, and Hamann and Canli suggest that affective dispositions and personality traits are able to explain individual differences in emotional reactivity and their underlying neural activity. Taking into account individual differences to explain performance measures might be a promising way to learn more about underlying mechanisms of emotion processing. Specifically, we are interested in whether measures of individual differences derived from emotion research are able to explain variability in individual data that discriminate happy and fear-related stimuli in word recognition.

A measure used to describe individual differences in emotion processing is the ability to recognize emotions from facial expressions, which has been shown to depend on the neural emotion processing network (Adolphs, 2002). Variability in measures of emotion recognition ability (ERA) have been related to differences in personality traits (Matsumoto et al., 2000), and tests of emotion recognition from facial expressions are widely used to describe deficits in ERA in psychological disorders, such as depression (e.g., Mikhailova, Vladimirova, Iznak, Tsusulkovskaya, & Sushko, 1996) and autism (e.g., Harms, Martin & Wallace, 2010). Hence, the ability to successfully recognize emotions from facial expressions can be taken as an index of the efficiency of underlying

neural mechanisms in emotion recognition, namely, perceptual abilities, conceptual knowledge, and simulation (Adolphs, 2002).

Besides such a global measure of ERA, states of positive and negative affect (Davidson, Irwin, Anderle & Kalin, 2003) and long-lasting emotional states that drive approach- and withdrawal-related behavior (Balconi & Mazza, 2009; Demaree, Everhart, Youngstrom, & Harrison, 2005; Gomez & Gomez, 2002) might also moderate the processing of emotional stimuli in a specific task context. The Positive and Negative Affect Schedule (PANAS; Watson, Clark, & Tellegen, 1988) is a questionnaire that is frequently used in clinical applications. Davidson et al. (2003) showed that individually experienced positive (PA) and negative affect (NA) modulate the processing of emotional stimuli. As an underlying mechanism, Ashby, Isen, and Turken (1999) proposed that elevated levels of brain dopamine are associated with PA, while NA is discussed in relation to the serotonergic system (Mitchell & Phillips, 2007).

Humans differ in their tendencies to initiate approach and inhibition behaviour (Carver & White, 1994; Demaree et al., 2005). This hypothesis was initially proposed by Gray (1981), who stated that both systems, a goal- and reward-orientated approach system and an inhibitory punishment avoiding system, are evident in mammals. These tendencies can be measured by the Behavioral Inhibition/ Behavioral Activation Scales (BIS/BAS; Carver & White, 1994), which are also known to moderate processing of emotional stimuli (e.g., Balconi & Mazza, 2009; Gomez & Gomez, 2002). Of note is that activity of behavioral approach and inhibition systems have been linked to differences in functioning of left and right brain hemispheres in emotion processing (Demaree et al., 2005). Accordingly, approach and withdrawal tendencies, as measured by BIS/BAS scales, have been linked to frontal hemispheric asymmetries in the alpha frequency band (FAA) measured by electroencephalography (EEG; Amodio, Master, Yee, & Taylor, 2008; Harmon-Jones & Allen, 1997; Sutton & Davidson, 1997). In general, decreased activation in the alpha band over cortical sites is related to an increase in cortical activation and allocation of cortical resources in these brain regions. FAA with greater power in the alpha band measured over right frontal cortical sites (compared to left frontal cortical sites, i.e. right-lateralized alpha activation), is therefore related to more left- than right-sided cortical activation (Briesemeister, Tamm, Heine, & Jacobs, 2013). Participants with such left-lateralized cortical activation have been shown to score higher on scales measuring BAS tendencies (Coan & Allen, 2003; Harmon-Jones & Allen, 1997). A pattern with right-lateralized cortical activation has been linked to higher scores on the BIS scale (Sutton & Davidson, 1997; but see Amodio et al., 2008; Harmon-Jones & Allen, 1997). FAA is also related to emotion regulation (Jackson et al., 2003) and emotional reactivity. Participants with a right-lateralized FAA

reported more intense positive affect in response to positive stimuli, and participants with a left-lateralized FAA reported more intense negative affect in response to negative stimuli (Wheeler, Davidson, & Tomarken, 1993). Amodio et al. (2008) and Tomer et al. (2014) illustrated a possible functional mechanism underlying the connection of FAA and differences in motivational behavior related to dopaminergic transmission: asymmetric striatal dopaminergic activity is thought to influence tonic frontal activity differentially between the hemispheres, thereby modulating motivational biases.

Similarly, based on findings in emotion word recognition, Kuchinke and Lux (2012) discussed that observed hemispheric differences in implicit emotion processing might depend on brain dopamine levels. Thus, the availability of dopamine seems to be a reasonable factor underlying different emotional responses and individual differences in emotion processing. A psychophysiological measure of central dopaminergic activity is the rate of spontaneous eye blinks (blinks; Depue, Luciana, Arbisi, Collins, & Leon, 1994; Karson, 1983; Slagter, Davidson, & Tomer, 2010). Over the nigrostriatal pathway, dopamine is known to activate basal ganglia that in turn are associated with locomotor activity (Gerfen, 2009). Heightened levels of dopamine in the striatum are therefore assumed to lead to increased motor activity (Beninger, 1983) that is mirrored in an increased blink rate (Karson, 1983; Slagter et al., 2010). While a healthy person blinks about 20 times per minute, people suffering from Parkinson's disease, which is characterized by low levels of dopamine, blink only about four times per minute. People suffering from schizophrenia, which is characterized by high levels of brain dopamine, blink significantly more often compared to healthy individuals (Karson, 1983).

Considering the aforementioned reviewed literature, a number of subject-specific variables can be identified that are known to modulate processing of emotional information at the level of individual differences, some of which point to personality traits and underlying neurobiological foundations. So far, no study has systematically analyzed their contributions to emotion processing. Individual differences likely contributed to previous ambiguous results. The present study exploratively examined the effects of individual differences in emotion processing as parametric regressors in emotion word recognition. We therefore measured behavioral responses in a standard paradigm of word recognition, the lexical decision task (LDT), using happy, neutral, and fear-related words. In LDTs, participants judge whether a letter string is a correct word or not (a nonword). Manipulations of emotional characteristics of words have been found to affect response times (RTs) and accuracy measures—even though these word characteristics are not relevant for the processing of the actual task itself. Thus, the emotional connotation of words is assumed to be processed incidentally, pointing to implicit processing of emotional information in this paradigm (Briesemeister,

Kuchinke, & Jacobs, 2011a; Hofmann, Kuchinke, Tamm, Vö, & Jacobs, 2009; Kanske & Kotz, 2007; Kousta, Vinson, & Vigliocco, 2009; Kuchinke et al., 2005).

One of the most reliable findings in emotion word recognition using the LDT are faster RTs for words of positive valence compared to neutral (Briesemeister et al., 2011a; Hofmann et al., 2009; Kanske & Kotz, 2007; Kousta et al., 2009; Kuchinke et al., 2005) and negative words (Briesemeister et al., 2011a; Kanske & Kotz, 2007; Kuchinke et al., 2005). Recent evidence suggests not only that positive words are processed faster than negative and neutral words but also that lexical access (i.e., the time it takes until a word is identified) is fastest in positive words (Kissler & Herbert, 2013). This facilitatory effect is also reflected in accuracy data where fewest errors are observed for positive words (Briesemeister et al., 2011a; Kousta et al., 2009; Kuchinke & Lux, 2012). While these findings based on positive valence seem reliable across studies, findings regarding negatively valenced words are less homogeneous. Some researchers find faster RTs for negatively valenced words compared to neutral words (Kanske & Kotz, 2007; Kousta et al., 2009); others find the opposite pattern, with larger RTs for negative compared to neutral words (Estes & Adelman, 2008; Larsen, Mercer, Balota, & Strube, 2008). Although ambiguous findings for negatively valenced words have been related to differences in word arousal levels (see Hofmann et al., 2009), studies that explicitly controlled for arousal still differed in their results (e.g., Briesemeister et al., 2011a, vs. Kousta et al., 2009). Again, individual differences in emotion processing have mainly not been considered in these studies. A study by Silva, Montant, Ponz, and Ziegler (2012) examined individual differences in disgust sensitivity in emotion word recognition. Both error rates and response times in a lexical decision task using disgust-related and neutral words were shown to depend on disgust sensitivity. Individuals with low disgust sensitivity revealed a facilitatory effect when processing disgust-related words, whereas an inhibitory effect was found in individuals with high disgust sensitivity. These results support our initial assumption and highlight the role of individual differences in emotion processing.

As the examination of average RTs and accuracy scores have methodologically been criticized as sharing several limitations, such as being prone to individual differences in response bias or response style (White, Ratcliff, Vasey, & McKoon, 2009), we decided to examine model-based individual parameters that are obtained by fitting diffusion models (DM) for each participant (see White et al., 2009). An advantage of the DM is that “unbiased estimates of an individual’s rate of evidence accumulation from stimuli (i.e., drift rate)” (White et al., 2009, p.186) are obtained because independent parameter estimates are computed for response bias and response criterion separation.

The DM (Ratcliff, 1978) is a computational sequential sample model wherein responses are modeled as the accumulation of noisy evidence over time until a response criterion is reached. Regarding LDTs, DMs are based on the assumption that evidence is accumulated over time until one of the boundaries, representing word or nonword decisions, is reached and the decision regarding the letter string is made. A DM analysis takes into account the RT distribution of each participant to estimate underlying parameters, namely, the so-called non-decision time, a boundary parameter, an a priori bias in starting point, and a drift rate parameter. An illustration of the DM is shown in Fig. 1.

Depending on experimental manipulations and task context, parameters are allowed to vary freely between different experimental conditions or are held constant across conditions (Vandekerckhove & Tuerlinckx, 2007). The non-decision-time parameter T_{er} covers stimulus encoding, preparatory processes, and motor responses (White, Ratcliff, & Starns, 2011). Typically, T_{er} is thought to be similar for both types of responses as long as they occur with the same frequency and no prior information about the upcoming trial is available to participants (Voss, Nagler, & Lerche, 2013). Additionally to T_{er} , across-trial variability of non-decision time $s_{T_{er}}$ can be modeled.

Boundary parameter a is an index of speed-accuracy tradeoffs. When the boundary width is narrower, the decision is reached quicker but is also more error prone, whereas, when the boundary is wider, more information is sampled until the decision criterion is reached, leading to high accuracy for decisions that take longer (Voss et al., 2013). When participants

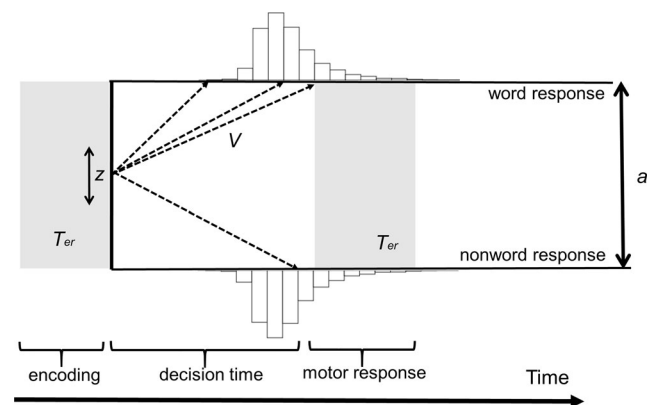


Fig. 1 An illustration of decision processes in the lexical decision task modeled by a DM: a indexes the boundary width that can vary in size, leading to more liberal or more conservative responses; z indexes the starting point of the decision process that is set to half of boundary parameter a , since both responses are equally often required. Dashed arrows index drift rates that either lead to a word or to a nonword response. Drift rates can vary in their steepness leading to faster or slower decisions. Corresponding response time distributions are shown in form of histograms at the response boundaries. The decision process is flanked by encoding processes and motor responses that are summarized under the non-decision-time parameter T_{er} and are here indicated by gray areas

are instructed to either emphasize speed or accuracy, their decision style is influenced to be either more conservative with a wider boundary (in case of an emphasis on accuracy) or more liberal with a narrower boundary (in case of an emphasis on speed), as was shown by White et al. (2011). For an equal emphasis on speed and accuracy, the boundary parameter can be held constant across experimental conditions.

Starting parameter z is related to a bias in responses, for example, when one of the responses in a two-choice reaction time task is valid more often than the other. In that case, participants might shift their starting points toward the response that occurs more frequently. When both responses occur with the same likelihood (as in the LDT), z is usually set at half of boundary parameter a , thereby modeling similar preparation for both responses (White et al., 2011). The across-trial variability in z , indexed by s_z , is also estimated by the model.

Drift rate parameter v indexes the average rate of approach to a boundary (White et al., 2011). Larger values indicate that a decision can be made relatively easily due to certain stimulus properties, resulting in a quicker arrival at the boundary. In DMs of LDTs, drift rates reflect the wordness of verbal stimuli (Ratcliff, Gomez, & McKoon, 2004; i.e., the ease with which they are identified as words). For example, processing of high-frequency words results in higher drift rates because the words are more familiar, while processing of low-frequency words results in lower drift rates. Based on the above assumptions, that word processing is facilitated for positive words, one would expect this result to be mirrored in higher drift rates for positive words. When drift rates are allowed to vary freely across different experimental conditions, variability in drift rate parameters can be used to examine differences in evidence accumulation between these conditions (Voss et al., 2013). Additionally, across-trial variability of drift rate is indexed by s_v and can also be estimated in the DM. Individual differences in DM parameters are captured by estimating an individual DM for each participant. Ratcliff et al. (2004) suggested that, for within-participant exploration, it is appropriate to hold all parameters constant across task conditions (i.e., for example, for different emotion conditions), except for the drift rate parameter.

In the present study, an LDT with emotional words is conducted using the happy, neutral, and fear-related word lists from Briesemeister et al. (2011a). It is expected that behavioral effects with faster RTs for happy compared to neutral and fear-related words, as well as lower error rates, are replicated. In addition, individual RT distributions are subjected to DM analyses. Based on the above considerations of a facilitated processing of positive words, higher drift rates are expected for lexical decisions to happy words compared to neutral and fear-related words. In addition, regression models for outcome parameters (RTs, error rates, and drift rates) will be computed to examine the variance explained in the main effect of emotion (discriminating between processing of happy and fear-

related words) by measures of individual differences in emotion processing. The goal is to explore the previously introduced variables of emotion processing in relation to outcome measures in an implicit emotion word recognition paradigm. If previous heterogeneities in the emotion effects of the LDT can be explained by individual differences in emotion processing, correlations between individual measures and emotion effects in outcome measures should be observed. The identification of relevant measures and the direction of their relation to implicit emotion processing are of specific interest.

Materials and method

Participants

Thirty-nine psychology students (34 female) between 17 and 45 years of age ($M = 23.05$, $SD = 6.57$), who reported to be right-handed, took part in the study. Participants were recruited via a notice on a bulletin board at the Ruhr-University Bochum and via social media. Participants were rewarded with course credit for participating in the study, and informed consent was obtained. The study was conducted in accordance with the Declaration of Helsinki and approved by the local ethics committee of the Faculty of Psychology at the Ruhr-University Bochum. Participants had normal or corrected-to normal vision and reported no history of neurological disorders.

Stimuli, apparatus, and data preparation

PANAS

The PANAS (Watson et al., 1988) includes a subscale for Positive Affect (PA) and a subscale for Negative Affect (NA), each comprising 10 self-report items. Participants were given the German version of the PANAS (Janke & Glöckner-Rist, 2014) in the form of a self-paced, computerized version that was programmed using Presentation software (Neurobehavioral Systems). Participants were instructed to indicate via button press to what extent a given adjective represented how they were currently feeling. Answers were given on a 5-point Likert scale ranging from *very slightly or not at all* to *extremely*. Completion of the questionnaire took approximately 5 minutes. Scores for PA and NA were each summed up in order to form composite scores for the two scales. Descriptive statistics of all variables of emotion processing can be seen in Table 1.

Emotion recognition ability (ERA)

Participants viewed pictures of humans displaying different basic emotions (Ekman & Friesen, 1971). Images of emotional faces displaying anger, fear, disgust, happiness, surprise, sadness, or a neutral facial expression were taken from the

Table 1 Descriptive statistics including empirical and theoretical ranges of the scores

	Mean	SD	Emp. range	Theor. range
PANAS PA	32.23	5.42	20–50	10–50
PANAS NA	16.41	8.89	10–41	10–50
ERA	32.21	2.17	26–35	0–35
BIS	15.13	2.36	9–21	7–28
BAS-Drive	6.44	1.76	4–11	4–16
BAS-Fun	8.49	2.33	5–13	4–16
BAS-RR	8.13	1.88	5–13	5–20
FAA	−0.10	0.29	−1.24–0.52	
Blinks	31.69	17.39	9–79	

Radboud faces database (Langner et al., 2010). A self-paced, computerized version of the task was programmed using Presentation software (Neurobehavioral Systems). All answer choices were displayed at the bottom of the screen, and participants used the mouse to click on the respective label. Three practice trials were given in advance, for which participants received feedback. The main task comprised 35 trials in pseudo-randomized order displaying faces of five individuals in each of the seven emotional expressions. Completion of the task took approximately 5 minutes. A sum score of correct responses across all displayed emotions was obtained for each participant.

BIS/BAS

The scores on BIS/BAS were measured using the self-report scales introduced by Carver and White (1994). BAS was divided into the subscales BAS-Drive (four items), measuring the persistent pursuit of goals; BAS Fun Seeking (BAS-Fun; four items), measuring desire for, and approach to, a reward; and BAS Reward Responsiveness (BAS-RR; five items), measuring positive responsiveness to a reward. The scale for BIS comprised seven items. A self-paced, computerized version (Presentation, Neurobehavioral Systems) of the German BIS/BAS questionnaire (Strobel, Beauducel, Debener, & Brocke, 2001) was used. Each statement was displayed in the center of the screen with four possible answers displayed at the bottom. Answers were given by button press on a 4-point Likert scale, ranging from *strongly agree* to *strongly disagree*. Completion of the questionnaire took approximately 5 minutes. For each of the scales—namely, BIS, BAS-Drive, BAS-Fun, and BAS-RR—sum scores were computed.

Frontal alpha asymmetries (FAA)

Recording of resting EEG using Brain Vision Recorder (Brain Products, Munich, Germany) took place in a dimly lit, sound-shielded and light-shielded room. Participants were seated on

a stool and asked to remain in a resting state, with their bodies relaxed, but to avoid movements. The following sequence was recorded (Harmon-Jones & Allen, 1997): 1 minute with eyes closed, 1 minute with eyes open, 1 minute with eyes closed, and 3 minutes with eyes open. EEG data were recorded from six Ag-AgCl electrodes (F3, F4, Fz, FCz, Cz, Pz) that were placed on an elastic cap according to the international 10–20 system and referenced to both mastoids. Impedances were kept below 5 k Ω . Data were sampled at 500 Hz. Vertical electrooculogram (EOG), with electrodes above and below the right eye, and horizontal EOG, from two electrodes at the outer canthi, were recorded. EEG data were preprocessed using Brain Vision Analyzer (Brain Products, Munich, Germany). Signals of EEG channels were filtered with a low cutoff filter at .5 Hz, a high cutoff filter at 70 Hz, and a notch filter at 50 Hz. A manual raw-data inspection was performed in order to remove any muscular artefacts. Channels F3 and F4 were re-referenced from averaged mastoids to Cz. A correction of eye movements was carried out using an Ocular Correction Independent Component Analysis that is implemented in Brain Vision Analyzer 2.0.4 and uses an Infomax algorithm. Eyes-closed and eyes-open data were analyzed in a combined 4-minute segment. EEG data of this segment were transformed using a Fourier wavelet to extract alpha band activation (8–13 Hz). This frequency range was subdivided into bins of .5 Hz range, for which alpha power magnitudes were computed. For each individual subject, alpha power magnitudes of all bins were compared and the value of maximal alpha power was extracted separately for F3 and F4 channels. After logarithmizing the values, the individual peak alpha power of channel F3 was subtracted from channel F4 to obtain an individual peak FAA score.

Spontaneous eye blinks (blinks)

The number of blinks were identified based on the recorded EOG during the 3-minute eyes-open interval of EEG measurement (see above). Participants were not aware that blinks were the target of this recording interval. Blinks were counted only during a 2-minute interval starting 30 seconds after the participants opened their eyes again (cf. Depue et al., 1994).

Lexical decision task (LDT)

Word material was taken from Briesemeister et al. (2011a), who reported faster RTs and fewer errors for happy compared to fear-related words in a sample of 21 participants. Seventy-five German nouns (four to six letters) were taken from the DENN-BAWL database (Briesemeister, Kuchinke, & Jacobs, 2011b) and matched on their level of arousal, number of letters, syllables, phonemes, orthographic neighbors, word frequency, imageability, and averaged bigram frequencies. Nouns differed in their emotional category and, thus, on the

respective valence dimension. Twenty-five happy, 25 neutral, and 25 fear-related nouns were selected (see Briesemeister et al., 2011a, Experiment 3). Nonwords were built by taking 75 different nouns of four to six letter lengths where one or two letters were replaced by different letters resulting in meaningless but pronounceable nonwords. In total, the word material consisted of 150 letter strings that were each presented once.

In the LDT, participants had to indicate via button press whether each presented letter string was a word or a nonword. Meanings of the right and left button were switched for half of the participants. All letter strings were presented on a computer screen in uppercase letters in 80 point Arial font using Presentation (Neurobehavioral Systems). Each trial started with the appearance of a fixation cross for 400 ms, followed by a letter string in black font against a light gray background. After 500 ms, the letter strings were masked by an array of hashtags that stayed on-screen for another 2,000 ms. Participants were asked to respond as fast and accurately as possible after presentation of the letter string and had time to indicate their answer until the hashtags disappeared. Before starting the experiment, participants completed 10 practice trials, during which the instructor was available to them for questions. After 75 trials, participants had a self-paced rest period. In total, task completion took approximately 15 minutes.

For data analysis, RTs for correct responses were submitted to a low cutoff criterion at 250 ms and an upper boundary of 3 *SD*. RTs and error rates were submitted to a repeated-measure analysis of variance, with emotion as within-subjects factor comprising three levels (happy, neutral, and fear-related words).

Procedure

First, participants took part in the resting state EEG recording to obtain measures of FAA as well as blinks. Afterwards, participants were seated in front of a 17-in. Dell computer screen, where they completed all following tasks, starting with PANAS and BIS/BAS questionnaires, that were followed by LDT and ERA. In between tasks, participants were always given the opportunity to rest. Besides the reported tasks, participants also completed two flanker tasks and a visual discrimination task, which are of no further interest in the context of this study. In total, participants remained in the laboratory for about 70 minutes.

Diffusion model

The DM was designed following the assumptions made by Ratcliff et al. (2004) who only let the drift rate vary freely across experimental conditions, that is, all DM parameters (z , T_{cr} , a , s_z , s_{Ter}) were held constant except for the drift rate

parameter ν , which was allowed to vary between happy, neutral, and fear-related conditions in the LDT. Response bias parameter z was set to half of boundary parameter a since no a priori biases in direction of either response were assumed (Voss et al., 2013). Individual DM parameters were estimated for each participant based on the individual RT distribution by computing multinomial likelihood functions using the DMAT toolbox (Vandekerckhove & Tuerlinckx, 2008). Behavioral outliers were removed beforehand by filtering out RTs faster than 250 ms and slower than 3 individual standard deviations above the individual mean RT (White et al., 2009). A repeated-measures ANOVA was carried out on the best fitting individual drift rate parameters for happy, neutral, and fear-related words.

Results

Response times (RTs)

There was a significant main effect of emotion in RTs, $F(2, 76) = 25.95$, $p < .001$, $\eta^2 = .406$, $1 - \beta > .999$, such that fastest responses were given for happy words ($M = 664.8$ ms, $SD = 129.4$ ms) followed by neutral ($M = 698.2$ ms, $SD = 132.2$ ms), and fear-related words ($M = 719.1$ ms, $SD = 150.7$ ms). Bonferroni-corrected pairwise comparisons revealed that RTs were significantly shorter for happy words compared to neutral and fear-related words ($ps < .001$), while neutral and fear-related words did not differ significantly from each other ($p = .052$).

Error rates

There was a significant main effect of emotion, $F(2, 76) = 49.86$, $p < .001$, $\eta^2 = .567$, $1 - \beta > .999$, such that most errors were made for fear-related words ($M = 12.8$ %, $SD = 7.9$), followed by neutral ($M = 4.6$ %, $SD = 4.3$) and happy words ($M = 3.1$ %, $SD = 2.8$). Bonferroni-corrected pairwise comparisons revealed that error rates for fear-related words differed significantly from error rates for neutral and happy words ($ps < .001$), while neutral and happy words did not differ significantly from each other ($p = .070$).

Diffusion model parameter estimates: Drift rates

The best fitting DM parameters are displayed in Table 2. There was a significant main effect of emotion on drift rates, $F(2, 76) = 8.707$, $p < .001$, $\eta^2 = .186$, $1 - \beta = .964$, such that drift rates were smallest for fear-related words ($M = .73$, $SD = .26$) followed by neutral words ($M = .76$, $SD = .28$) and largest for happy words ($M = .90$, $SD = .39$). Bonferroni-corrected pairwise comparisons revealed that drift rates for happy words differed significantly from drift rates of both neutral ($p < .001$)

Table 2 Diffusion model parameters: means and standard deviations in parenthesis. All parameters except for drift rate ν were held constant across the four conditions and are therefore the same for all of them

	a	T_{er}	s_{Ter}	z	s_z	η	ν
Happy	.279 (.079)	.485 (.096)	.152 (.124)	.167 (.053)	.066 (.069)	.064 (.067)	.873 (.676)
Fear							.581 (.299)
Neutral							.587 (.201)
Nonwords							-.665 (.392)

and fear-related words ($p = .017$), with no significant difference between the latter two ($p > .999$). Model predictions for the different emotion categories are displayed in the quantile probability plots in Fig. 2.

Analysis of individual differences

A first explorative correlation analysis was carried out based on individual difference values between happy and neutral, happy and fear-related, and fear-related and neutral conditions. Difference scores were calculated for RTs, error rates, and drift rates and correlated with all nine variables of emotion processing. Additionally, correlations between emotion processing variables and DM estimates of individual response style (boundary parameter a , non-decision-time T_{er} ; cf. White et al., 2009) as well as overall mean RTs and error rates were computed (see Table 3).

Next, three separate multiple linear regression analyses were conducted for RTs, error rates, and drift parameters as dependent variables in order to predict individual emotional effects. For this purpose the main effect of emotion in the dependent variables, namely the difference between processing of happy and fear-related words (H-F), was taken as the to-be-predicted measure. Nine centered predicting variables (blinks, BIS, BAS-Drive, BAS-Fun, BAS-RR, ERA, FAA, PA, NA) were entered step-wise into the regression models¹ in order to explore their predictive value on outcome variables using SPSS (p -to-enter = .05, p -to-stay = .10). Power values were computed post hoc using G*Power (Version 3.1.9.2; Faul, Erdfelder, Lang, & Buchner, 2007).

Happy-fear RTs (H-F_{RT})

The final regression model significantly predicted H-F_{RT} differences, $F(2, 36) = 4.97$, $p = .012$, $R^2 = .216$, $1 - \beta = .891$. Two variables were included in the final model. As a first predictor, BAS-Drive was entered into the model ($t = -2.22$, $p = .033$, $\beta = -.327$). The second significant predictor was blinks ($t = -2.19$, $p = .035$, $\beta = -.323$). Together, both variables of emotion processing explained 21.6 % of variance in

¹ All multiple regression analyses were also carried out with a backward elimination procedure, which yielded identical results.

H-F_{RT} differences. No further predictor was entered into the regression model. The negative beta values of both predictors indicate that with increasing values of BAS-Drive and blinks larger (more negative) individual H-F_{RT} differences were observed (see Fig. 3).

Happy-fear error rates (H-F_{err})

The stepwise multiple regression approach could not identify a significant predictor of individual H-F_{err} differences among the nine predictor variables.

Happy-fear drift rates (H-F_v)

Only one variable was entered into the final regression model that significantly predicted individual differences in DM drift rates between happy and fear-related words, $F(1, 37) = 6.26$, $p = .017$, $R^2 = .145$, $1 - \beta = .707$. ERA ($t = -2.50$, $p = .017$, $\beta = -.380$) explained 14.5 % of variance in H-F_v. No further predictor was entered into the regression model. The negative beta value for ERA indicates smaller H-F_v differences for participants who have better ERA (see Fig. 3).

Discussion

The study was designed to exploratively examine and explain variables contributing to individual differences in emotion word recognition. As a first result, the main effect of emotion, with differences between happy and fear-related words in RTs and error rates, was replicated using the same stimulus material as Briesemeister et al. (2011a). Overall, the pattern replicates earlier findings of implicit processing of a word's emotional connotation in word recognition.

A facilitatory effect of positive compared to neutral and negative words in the LDT was replicated for happy words (Briesemeister et al., 2011a; Hofmann et al., 2009; Kousta et al., 2009). A speed advantage of positive material has been discussed in relation to a higher density and a larger number of associations among positive stimuli (Unkelbach, Fiedler, Bayer, Stegmüller, & Danner, 2008). Because a top-down influence of the associative structure of to-be-processed items is controversially discussed in case of the LDT (e.g.,

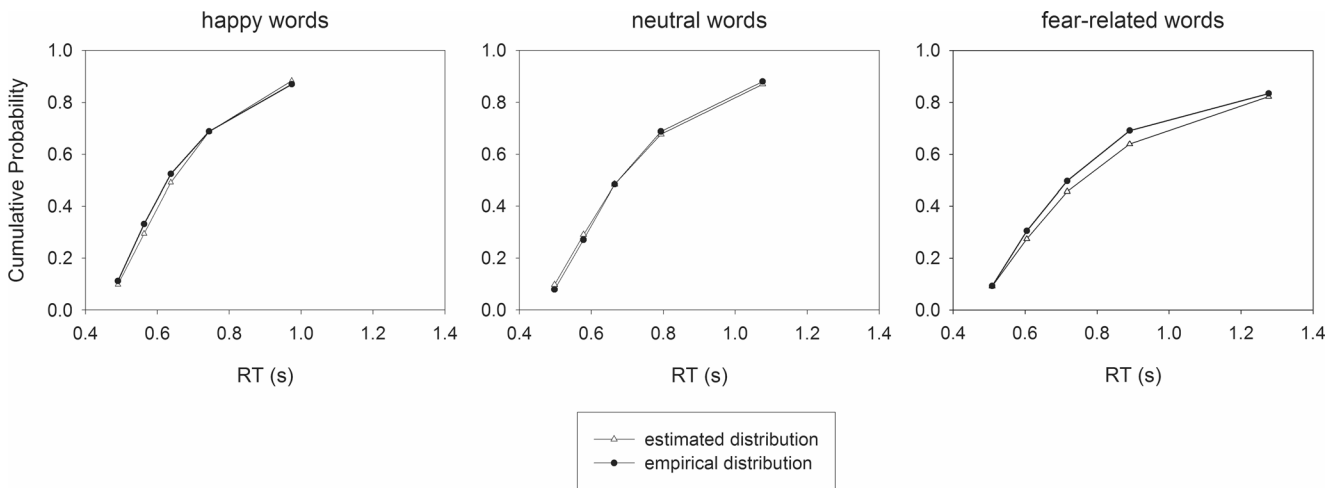


Fig. 2 Quantile probability plots displaying cumulative response-time distributions of estimated and empirical data .1, .3, .5, .7, and .9 quantiles are marked by circles for empirical data and triangles for theoretical data. The figures show the probability of correct responses depending on response times

Kuchinke et al., 2005), the density and similarity of valenced material alone might not be sufficient to explain a positivity advantage. Accordingly, Kuchinke and Lux (2012) were able to provide some evidence linking the positivity advantage in word recognition to dopaminergic transmission and the specificity of the language-processing left-brain hemisphere.

An emotion effect was also evident in error rates replicating the findings of Briesemeister et al. (2011a) of larger error rates for fear-related compared to happy and neutral words. Estes and Adelman (2008) reported slowed responses for negative stimuli and discussed them in relation to automatic vigilance models, which state that attention is disengaged more slowly from stimuli of a negative emotion category compared to stimuli of neutral or positive categories. Since we found only a

trend toward slowed RTs for fear-related compared to neutral words, participants might have tried to avoid a slowdown of responses, thereby accepting the cost of larger error rates in return. A nonsignificant difference in RTs between negative (here, fear-related) and neutral words is not always found in the literature. It seems likely that this finding is due to the use of discrete emotion categories. Briesemeister et al. (2011a), who in addition to fear-related words also investigated disgust- and anger-related words corresponding to the negative spectrum, found significantly slower RTs for disgust-related compared to neutral words. No significant differences were evident between anger and fear-related compared to neutral words. With the present exploratory study, we have now first evidence, that besides the stimulus selection also

Table 3 Correlation table: RT = mean response times; ER = mean error rates; a = boundary parameter; T_{er} = non-decision time; H-F = difference between happy and fear related words; H-N = difference between happy and neutral words; F-N = difference between fear-related and neutral

words; v = drift rate of the diffusion model; RT = response time; err = error rates; FAA = frontal α -asymmetries; ERA = Emotion Regulation Ability; PA = Positive Affect subscale of the PANAS; NA = Negative Affect subscale of the PANAS

	PA	NA	ERA	BIS	BAS-Drive	BAS-Fun	BAS-RR	FAA	Blinks
RT	.021	.040	.210	-.121	-.100	.014	-.102	-.062	.147
ER	.060	.051	-.137	.036	.049	-.016	-.165	-.116	.190
a	-.106	-.336*	-.013	-.070	.037	-.089	.027	-.256	.012
T_{er}	.148	.176	.167	-.067	-.091	.087	-.150	.194	.048
H-F _v	.175	.215	-.380*	-.128	.094	.129	.067	.068	.048
H-N _v	.005	.191	-.215	.134	.138	.028	.107	-.021	.031
F-N _v	-.278	-.183	.430*	.323*	-.034	-.184	-.017	-.128	-.052
H-F _{RT}	-.009	-.186	.281	-.099	-.334*	-.158	.020	.177	-.331*
H-N _{RT}	.013	-.067	.243	-.096	.051	.146	-.180	.000	-.249
F-N _{RT}	.017	.165	-.173	.055	.388*	.249	-.117	-.191	.224
H-F _{err}	-.182	-.200	.087	.012	.100	.009	.205	.149	-.227
H-N _{err}	.030	-.294	-.083	-.059	-.025	.078	-.048	-.069	-.160
F-N _{err}	.200	.039	-.133	-.045	-.114	.034	-.232	-.187	.140

Significant correlations ($p < .05$) are written in bold font and marked by*

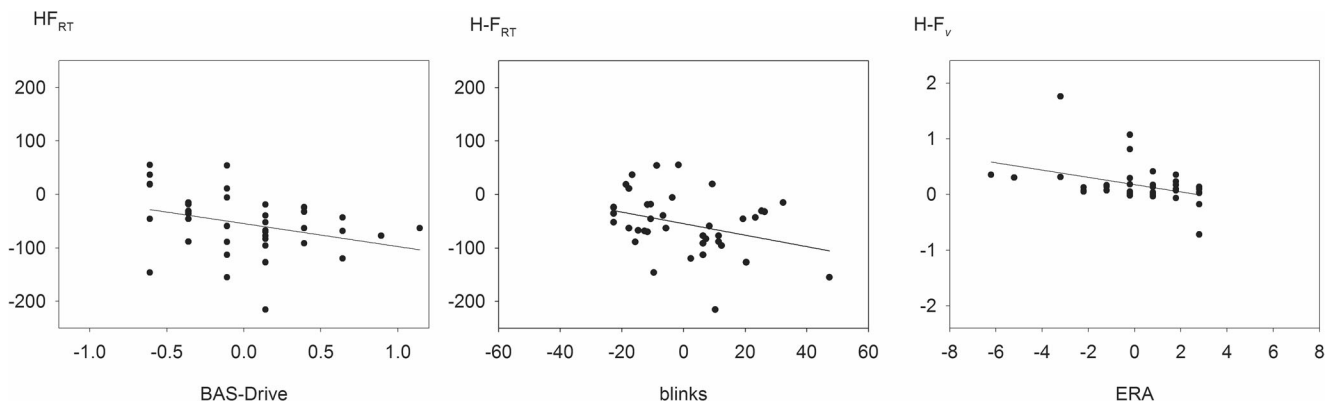


Fig. 3 Scatter plots with regression lines of centered predictor variables that were related to differences in happy-fear outcome measures

individual variables of emotion processing contribute to these emotion effects.

A further main finding was revealed by DM analysis: Results regarding drift rate parameter ν complete the above pattern by revealing that highest rates of information accumulation (i.e., higher drift rates) were found for happy words compared to neutral and fear-related words (that did not differ from each other). As we are not aware of any study examining drift rate differences in word recognition related to implicitly processed emotional information, this is first evidence that drift rate, an “unbiased estimate” (White et al., 2009), captures emotion differences. Unbiased thereby refers to estimations of drift rates in the LDT that are not affected by individual response biases (like a speed-accuracy trade-off between RTs and error rates), as these are estimated separately in boundary parameter a (Voss et al., 2013).

Based on the results of the emotion effect on drift rates, it becomes clearer that it is the positivity of words that drives the effect toward a processing advantage rather than a slowdown of words with a negative connotation. Thus, a positivity advantage with higher drift rates indicating a higher rate of evidence accumulation in happy compared to neutral and fear-related words is visible. As there is no evidence of a disadvantage for negative compared to neutral words in the estimated drift rate parameters, we believe that the trend toward RT slowing and higher error rates for negative words as discussed above are not in line with further decreased information accumulation. It seems likely that these effects for negative, fear-related words are mirrored in adjusted non-decision times, speed-accuracy trade-offs, or response bias measures following stimulus presentation. Shifts in response bias have been observed in the LDT (e.g., Windmann, Daum, & Güntürkün, 2002) and because these DM parameters of response style are set for whole conditions (i.e., stimulus lists) in the present DM, future studies need to address how such assumed within-trial changes based on emotional information could be modeled in the DM.

Drift rate differences have previously been discussed to be related to stimulus familiarity. Stimulus familiarity refers to

subjective ratings of how familiar a word is as an alternative to objective corpus-based measures like word frequency. Both variables share some conceptual overlap (Gernsbacher, 1984) and often show similar effects in the response times (e.g. Kousta et al., 2009). Accordingly, Ratcliff et al. (2004) reported an influence of word frequency on drift rates. Because in the present study word material was matched on the frequency dimension, word emotionality also appears to be a relevant factor influencing drift rates. Ratcliff et al. (2004) called this an effect of wordness, that is, words with higher frequency appear more word-like and thus evidence in favor of a “WORD” response is accumulated faster. Similarly, it has been discussed based on models of word recognition that positive words are identified fastest (Kissler & Herbert, 2013). Interestingly, the only computational model of the LDT that also incorporates emotion effects, the MROME (extended multiple read-out model; Kuchinke, 2007), successfully simulates faster RTs of emotional words by enhanced lexical activity at a proposed word level based on an affective mechanism operating on associated affective information. Enhanced model-predicted lexical activity in such computational models of word recognition is commonly assumed to mirror wordness (e.g., Braun et al., 2006).

In line with our initial hypotheses, individual variables of emotion processing affected the main effect of emotion in implicit emotion processing in the LDT, as revealed by the multiple regression approach. For this exploration, difference scores between happy and fear-related words were computed for outcome measures of the LDT and subjected to regression analyses in order to identify relevant predictors.

Results of regression analysis on RTs revealed that BAS-Drive was the variable that explained most of the variance regarding H-F_{RT} differences. RTs for happy words were generally shorter compared to RTs to fear-related words, resulting in negative difference scores on average. The negative relation of H-F_{RT} differences to BAS-Drive scores revealed that participants with larger BAS-Drive scores showed greater H-F_{RT} differences. BAS-Drive scores are assumed to capture effects of persistency in pursuing desired goals (Carver & White,

1994). Additionally taking into account the correlation analysis where $F-N_{RT}$ differences correlated positively with BAS-Drive scores, it seems likely that the results on $H-F_{RT}$ differences were rather driven by the relation of BAS-Drive in response to fear-related words such that participants with large scores in BAS-Drive seem to have longer RTs for fear-related words compared to participants with lower BAS-Drive scores. This finding seems related to the automatic vigilance hypothesis in the sense that participants who show higher goal-orientedness also process stimuli more effectively by assigning more attention to their processing, which then for fear-related words results in a larger effect of automatic vigilance evident in slower responses compared to participants who do not process the stimuli with as much goal-driven attention.

The number of blinks, which has been introduced as indicator of brain dopamine levels (e.g., Slagter et al., 2010), was a second relevant variable predicting $H-F_{RT}$ differences. The negative correlation of $H-F_{RT}$ differences with the number of blinks suggests that greater differences in RTs were related to a higher blink rate. Taking into account the results of Kuchinke and Lux (2012), where an indirect enhancement of dopamine levels in the striatum was achieved that resulted in a processing advantage for positive words, it seems likely that in the present study a higher dopamine availability at the brain level (as indicated by blink rate) had a facilitatory influence on processing of positive stimuli, in this case happy words. This assumption gains additional support from a study by Epstein et al. (2006), who found less striatal activation in response to positive words in a group of depressed subjects compared to healthy controls. Behaviorally, depressed subjects did not show the typical effect of faster responses to positive versus neutral words that was evident in healthy controls, suggesting a link of striatal activation to facilitated processing of positive words mediated by brain dopamine levels. This result is further evidence for our hypothesis that the processing advantage for happy (or positive) words is related to striatal activation and individual differences in brain dopamine levels (e.g., Kuchinke & Lux, 2012).

A different predictor variable was identified in the stepwise multiple regression on drift rate parameters where ERA significantly predicted the emotion effect. At a first glance, this result supports Ratcliff's assumptions that DM parameters and in particular the unbiased estimates of evidence accumulation capture different aspects of information processing than average RTs and error rate measures (Ratcliff et al., 2004). Drift rate parameters mirror differences in stimulus quality, such as differences in word frequency (Ratcliff et al., 2004). However, as was already evident in the main effect of emotion, drift rates also reflect differences in emotional valence of words when frequency is controlled for.

The negative beta for ERA shows that participants with better emotion recognition abilities had comparable drift rates

for happy and fear-related words while participants low in ERA exhibited larger $H-F_v$ differences. Taking into account the positive correlation of $F-N_v$ differences and ERA (see Table 3), participants who were better in accumulating evidence for fear-related words also appeared to be better in recognizing emotions from faces. Four of the seven emotions in ERA are negative (Ekman & Friesen, 1971), so the task largely relies on the discrimination among different negative emotions. Participants better in accumulating information related to negative items might benefit from this ability in both tasks, LDT and ERA. We believe that these findings illustrate the importance of taking into account diffusion models when studying individual differences in emotional processing.

As a main result different variables were found to predict emotion processing differences in RTs and drift rates, respectively. Both variables share some functional overlap and both revealed a main effect of emotion (i.e., a significant difference between happy and fear-related words). An important difference between RTs and the model-predicted drift rates is that the drift rate parameter particularly captures information accumulation with respect to the decision/response to be made. Response times, in contrast, also contain encoding, preparatory and motor execution processes (see Fig. 1) that are summarized under the non-decision-time parameter T_{er} in the DM. It seems likely that effects of emotion processing variables on these processes are able to mask effects of ERA in the response times.

Likewise, since the variables BAS-Drive and the number of spontaneous eye-blinks do not predict information accumulation in the drift rate analysis of the DM, it becomes more likely that both effects on response times are driven by either early encoding-related interactions or effects at the level of response execution. Estimating the T_{er} parameter does not allow for separate, more fine-grained analyses of all implied sub-processes, and again, some of the effects might be masked by the influence of other variables.

Unfortunately, it is therefore not possible to examine these effects with a DM. To solve this problem, simulations using hybrids of, for example, interactive activation models of visual word recognition that model responses in the lexical decision task (for a review, see Hofmann & Jacobs, 2014) and models of information accumulation using diffusion processes (Ratcliff et al., 2004) seem more appropriate (cf. Dufau, Grainger, & Ziegler, 2012, for such a hybrid).

Differences in $H-F_{err}$ were not predicted by any of the nine examined emotion variables, suggesting that statistical power was too low to detect relations that have smaller effect sizes. This could be overcome by examining larger samples in future studies. Also, error rates in response to happy words were very low; therefore, possible relations between happy–fear differences in error rates and emotion variables might be masked by this floor effect. An alternative explanation is that differences in errors are less well explained by emotion processing and

instead could rely more on individual differences in cognitive processing styles, such as conflict monitoring or inhibition.

A number of emotion processing variables did not explain variance in processing differences between happy and fear-related words: states NA and PA as measured by the PANAS did not have any effect, suggesting that the current affective state does not affect implicit processing of emotional information in the LDT, at least in this healthy sample of psychology students. Additionally, FAA as well as BIS scores and scores on further BAS subscales (BAS-Fun, BAS-RR) were not found to interfere with emotion processing. Trait FAA have been linked to differences in approach motivation (Coan & Allen, 2003; Harmon-Jones & Allen, 1997) and asymmetries in dopaminergic activity (Amodio et al., 2008; Tomer et al., 2014). In the present study, FAA have been recorded at rest. Measuring individual changes in state FAA (cf. Ohme, Reykowska, Wiener, & Choromanska, 2010) directly in response to happy and fear-related words in the LDT might have revealed approach and withdrawal tendencies related to emotion processing. Such correlations were not evident in trait FAA. Another possible explanation for the findings are that implicit emotion processing as in the LDT might not be modulated by approach motivation to such an extent that individual differences in FAA and on all BIS and BAS subscales are evident in emotion-related performance differences. Our findings on BIS/BAS differ from the Gomez and Gomez (2002) study, which found that BIS was positively correlated with processing of negative words and BAS was positively correlated to processing of positive words in an implicit word fragmentation and two explicit processing tasks. However, the stimulus material in these experiments have not been controlled for word frequency or number of orthographic neighbors, making it difficult to compare these results with the present ones. In general, a task dependency of emotion effects in word recognition is well documented (e.g., Hinojosa, Albert, López-Martín, & Carretié, 2014). Based on Hinojosa et al. (2014), who discuss a likely reinforcement of negative information by higher order stimulus evaluation processes in explicit tasks, one could predict larger effects in future studies using an explicit emotion processing paradigm.

We would like to note, that the relatively low number of participants (for a behavioral study, but not compared to other EEG/FAA studies; e.g., Amodio et al., 2008) might constrain the number of effects we were able to detect. Also, all of the participants were psychology students from the same university, suggesting that the sample might be relatively homogeneous regarding their range of individual differences in emotion processing. In light of these limitations, it is even more remarkable that some of the relations we found between individual measures and emotion processing were pronounced enough to be evident in this group of subjects.

The study showed that individual differences in emotion processing were related to implicit emotion processing in the

LDT. H-F_{RT} differences were differentially predicted by individual difference variables: Whereas higher BAS-Drive scores appeared to be related to a specific slowdown in processing of fear-related words, probably due to larger effects of automatic vigilance, the blink rate, indexing brain dopamine levels, appeared to be associated to a processing advantage of happy words. Analyses of DM data showed for the first time that effects of word emotionality were captured by drift rates even though word-frequency was controlled for. Additionally, ERA predicted H-F_v differences pointing to a similar way of information accumulation for negative items in ERA and LDT that seem dissociable from effects on non-decision-time-related processes present in the response time data. The findings emphasize the importance of considering individual differences in emotion processing and highlight the role of diffusion model parameters in the examination of behavioral data and particularly, of individual differences. Taking into account individual differences can be crucial in interpreting heterogeneous results in the literature. These individual variables might in fact provide an explanation for the empirical heterogeneity. Furthermore, using combinations of behavioral and DM data might help to dissociate the contributions and the specific effects the variables have on the processes involved in emotion word recognition.

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