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What a Feeling!?
Perspectives on Affective Word Processing...

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Summary

While early studies that investigated the processes underlying normal reading and how these are affected by words with strong affective connotations focused on differences concerning varying degrees of positivity or negativity, the affective word processing literature more recently evolved from this rather simple way of thinking. More elaborated theories of human emotion and more complex research designs have been used to understand affective word processing. The results, however, are still inconclusive.

The present work introduces a novel perspective into affective word processing, suggesting that emotions are not (only) characterized on a two-dimensional affective space comprising valence and arousal, but are best explained in terms of functionally discrete emotions. Several experiments were conducted, providing evidence that a) subjects can differentiate at least five discrete emotions when rating words, b) words that are controlled for valence and arousal still affect lexical decision response times and error rates when manipulated on specific discrete emotions, and c) that these effects are stable and comparable across at least German and English language. In a second step, two experiments with words orthogonally manipulated on discrete emotions (i.e. happiness) and on the valence dimension (i.e. positivity) at the same time show that both variables independently affect word processing variance on the behavioral and the neurophysiological level. Happiness effects on the N100 EEG component preceded positivity effects, which were visible on the N400 and the late positive complex. Moreover, an fMRI study documented that the happiness manipulation recruits the right amygdala and the cerebellum, while the processing of positivity related words relies on medial and inferior frontal regions.

Taken together, these results suggest that affective word processing is much more complex than initially thought. The effects are in line with predictions of the hierarchical emotion model proposed by Panksepp (1998), however, which is used to discuss the future of affective word processing and to make further predictions for additional research.

Zusammenfassung

Während sich frühe Studien zu Prozessen des normalen Lesens und dem Effekt emotional eingefärbter Worte hauptsächlich auf die Unterscheidung verschieden starker positiver und negativer Konnotationen beschränkten, hat sich die affektive Wortverarbeitung in den letzten Jahren zunehmend von dieser simplen Sichtweise entfernt. Ausgearbeitete Emotionstheorien und komplexe Studiendesigns wurden eingesetzt, um den Einfluss emotionaler Information aufs Lesen zu verstehen. Die Ergebnisse sind allerdings unschlüssig.

Die vorliegende Arbeit führt deshalb eine neue Perspektive ein: Emotionen sind nicht (nur) durch einen zweidimensionalen affektiven Raum bestehend aus Valenz und Arousal charakterisiert, sondern können als funktional diskrete Emotionen beschrieben werden. Verschiedene Experimente wurde durchgeführt, deren Ergebnisse nahelegen, dass a) Versuchspersonen problemlos mindestens fünf verschiedene diskrete Emotionen bei Wortkategorisierungen unterscheiden können, b) Wörter, die sich bezüglich Valenz und Arousal nicht unterscheiden, die aber hinsichtlich diskreter Emotionen manipuliert sind, noch immer die Verarbeitungsgeschwindigkeit und Fehlerfreiheit bei einer lexikalischen Entscheidungsaufgabe beeinflussen und dass c) diese Effekte stabil und vergleichbar für mindestens die Deutsche und Englische Sprache sind. In zwei weiteren Experimenten wurde anhand orthogonal manipulierter Wörter gezeigt, dass sowohl diskrete Emotionen (Freude) als auch affektive Dimensionen (Positivität) unabhängige Effekte auf Verhaltens- und neurophysiologische Daten zeigen. Erstere beeinflussten die N100 EEG Komponente, letztere sind erst auf der nachfolgenden N400 und dem late positive complex nachweisbar. Zudem zeigte eine fMRT Studie, dass die Freude-Manipulation Aktivität in der rechten Amygdala und im Kleinhirn moduliert, während Positivitäts-Effekte auf Aktivität in medialen und inferioren frontalen Strukturen beruhen.

Zusammengefasst scheint die affektive Wortverarbeitung komplexer als ursprünglich angenommen. Die Effekte sind jedoch im Einklang mit dem hierarchischen Emotionsmodell von Panksepp (1998), welches in der abschließenden Diskussion zugrunde gelegt und dessen spezifische Vorhersagen besprochen werden.

Introduction to Affective Word Processing

Chapter 01

From a scientific point of view, the ability to read and understand written words is one of the most important and complex cognitive skills in modern societies. Newspapers, print ads, street signs, text messages and the internet, which have become our constant companion thanks to modern mobile technology, all rely on written words to guide us through our every day lives. Only few hundred milliseconds are necessary from the first fixation on a given word to its full mental representation (Hauk, Davis, Ford, Pulvermüller & Marslen-Wilson, 2006; Pylkkänen & Marantz, 2003; Sereno & Rayner, 2003), which is why we often forget that even the highly automated identification of a single word in a line of text relies on the complicated convergence of sensory, orthographic, phonological, morphological, semantic and syntactical information. Therefore when being interested in the functional processes underlying reading performance, a reductionist approach seems necessary.

A common way to reduce complexity in reading research is to focus on small meaningful text units, that is single words. Most empirical studies that investigate reading hence rely on one of four single word identification tasks, that is naming, where subjects have to read out loud a presented word (Coltheart, Rastle, Perry, Langdon & Ziegler, 2001), progressive demasking, where masked words are presented and the mask is slowly removed until the subjects are able to identify the word (Dufau, Stevens & Grainger, 2008), silent reading, where subjects read single words without behavioral response while their electroencephalogram (EEG) is recorded (Herbert, Junghofer & Kissler, 2008), and, finally, the lexical decision task (LDT, Grainger & Jacobs, 1996). The LDT, where subjects have to decide whether a presented letter string is a word or an orthographically illegal nonword, has become the standard paradigm in the visual word recognition literature, with more than 57 variables known by now to significantly affect lexical decision response times (LDRT, Graf, Nagler & Jacobs, 2005). Word length and word frequency, for example, the two most important independent variables, together account for most of the overall LDRT variance (New, Ferrand, Pallier & Brysbaert, 2006).

Being one of the most used tasks in cognitive psychology, several computational models have been proposed to explain the processes underlying successful lexical decisions (Coltheart, Curtis, Atkins & Haller, 1993; Coltheart et al., 2001; Grainger & Jacobs, 1996; Jacobs, Graf & Kinder, 2003). Most of these models focus on cognitive processes alone, however, thereby neglecting or at least ignoring the well documented effects of affective content – with the extended multiple read-out model (MROMe, see chapter 5 in Kuchinke, 2007) being one of the few notable exceptions. Nested upon its predecessor (Grainger & Jacobs, 1996), the MROMe is a localist connectionist computational model that consists of four interconnected levels: a feature level, a letter level and a word level representing the mental lexicon, all of which are already incorporated in the non-affective initial version of the MROM, complemented by an early affective evaluation mechanism. The processing of emotional words is then best described as follows: When the activation of the lower levels reaches the word level, activating a word unit associated with affective information there, this single unit activation is being enhanced by the affective evaluation mechanism, which in turn leads to the prediction of faster word recognition for emotionally valenced but not neutral words.

The MROMe's affective evaluation mechanism is explicitly based on the automatic evaluation hypothesis (Anderson & Phelps, 2001; Bargh, 1992; Murphy & Zajonc, 1993; Windmann, Daum & Günturkün, 2002), which assumes that affective information is processed with minimal stimulus input at early stages of perception. Numerous studies have contrasted words having a positive connotation (e.g. “LIEBE”, engl.: “LOVE”) with neutral words (e.g. “BAUM”, engl.: “TREE”) and found faster and more accurate processing for the former. To date, facilitated processing of positive words is the best replicated effect in affective word recognition, known for English (Citron, 2011; Holtgraves & Felton, 2011; Kousta, Vinson & Vigliocco, 2009; Larsen, Mercer, Balota & Strube, 2008; Scott, O'Donnell, Leuthold & Sereno, 2009; Scott, O'Donnell & Sereno, 2014; Siegle, Granholm, Ingram & Matt, 2001; Yap & Seow, 2014), Spanish (Carretié et al., 2008; Hinojosa, Méndez-Bértolo & Pozo, 2010), and German words alike (Briesemeister, Kuchinke & Jacobs, 2012; Hofmann, Kuchinke, Tamm, Võ & Jacobs, 2009; Kanske & Kotz, 2007; Kissler & Koessler, 2010; Kuchinke et al., 2005; Palazova, Mantwill, Sommer & Schacht, 2011; Recio, Conrad, Hansen & Jacobs, 2014; Schacht & Sommer, 2009a; 2009b). Moreover, the effect seems to be independent of word frequency (Kuchinke, Võ, Hofmann & Jacobs, 2007; Scott et al., 2009). Negatively valenced words, which represent the other extreme end of emotional valence, have also been found to be processed faster and more accurate than neutral words in the past (Eviatar & Zaidel, 1991; Kanske & Kotz, 2007; Kousta et al., 2009; Kuchinke et al., 2007; Palazova et al., 2011; Schacht & Sommer, 2009a; 2009b; Scott et al., 2009), suggesting that facilitated processing is not limited to positivity. All these data are in support of the automatic evaluation hypothesis and the MROMe - but there are also contradictory results.

Several experimental studies using the LDT report slower LDRTs for negative words when compared to both, positive (Bayer, Sommer & Schacht, 2011; Estes & Verges, 2008) and especially to neutral stimuli (Algom, Chajut & Lev, 2004; Briesemeister et al., 2012; Carretié et al., 2008; Citron, 2011; Estes & Adelman, 2008a; Larsen et al., 2008). These results have been replicated numerous times, especially in studies using large corpora that promise more reliability than experiments with limited item sets and small sample sizes (Estes & Adelman, 2008a; Larsen et al., 2008). This is a serious challenge for the automatic evaluation hypothesis, the most widely accepted explanation being that it is crucial for survival to quickly detect and evaluate stimuli that might have undesirable consequences. Negative words therefore automatically capture our attention to a greater extend than neutral or positive words, even in cases when the attentional resources are needed elsewhere (Wentura, Rothermund, Bak, 2003). This so called automatic vigilance hypothesis (Pratto & John, 1991) suggests that the quick and automatic evaluation of negative stimuli leads to a withdrawal of attention from the actual task demands, that is the lexical decision, and thus to prolonged response times caused by a deeper processing of the (negative) word itself. Obviously, the automatic evaluation hypothesis and the automatic vigilance hypothesis are contradictory, and neither hypothesis can account for the entire spectrum of published results. Thus, by the time this research project started in 2009, the mostly data driven approach dominating the affective word processing literature was step by step complemented by a more theory driven approach.

Several recent studies suggest that it is not the affective meaning of a word that interferes with the lexical processing, but that the actual visual word form itself can become a conditioned emotional stimulus that affects the word recognition process (Bayer, Sommer & Schacht, 2012; Beckes, Coan & Morris, 2013; Fritsch & Kuchinke, 2013, see also Barrett, Lindquist & Gendron, 2007 for an introduction to the contextual learning hypothesis). Fritsch and Kuchinke (2013), for example, demonstrated that meaningless letter strings that have previously been paired with emotionally arousing pictures several times in an affective conditioning paradigm elicit event-related potential (ERP) effects that are comparable to known effects elicited by affective words. Other work suggests that the evolutionary young process of reading might have been built upon already existing affective neural structures, which now causes a neural re-use (Ponz, Montant, Liegeois-Chauvel, Silva, Braun, Jacobs & Ziegler, 2013a; see also Anderson, 2010). While it is not within the scope the present work to investigate the appropriateness of the contextual learning and the neural re-use hypotheses, both frameworks agree that affective word processing might actually be functionally and causally linked to emotion processing brain structures. If this is true, affective word processing would be a suitable experimental paradigm to test theories of human emotion – and by doing so, explain the existing contradictory results.

Testing Emotion Theories with Affective Word Recognition

While initial affective word recognition research contrasted “emotional” with “neutral” words or “positive” with “negative” words, thus applying a very limited concept of affective information, even the most simple current emotion models suggest that human affect[1] is best described with a multi-dimensional space. Most commonly, it is assumed that two independent dimensions underlie affective processing (e.g. Bradley & Lang, 2000; Russell, 2003): emotional valence and arousal. Emotional *valence* refers to the hedonic value of the stimulus, ranging from a positive to a negative pole with a neutral midpoint or range. Earlier affective word processing research mostly focused exclusively on this dimension, presenting the mixed results introduced above. Emotional *arousal*, the second affective dimension, is meant to index the excitement or intensity of the emotion, ranging from low to high arousing or sometimes from calming to exciting. Arousal is assumed to be orthogonal to emotional valence, but when subjects are asked to judge valence and arousal of one and the same stimulus, often a U-shaped relationship with extremely valenced stimuli also being more arousing than neutral stimuli is observed, which is especially prominent at the negative end of the valence scale (Bradley & Lang, 1999; Redondo, Fraga, Padrón & Comesana 2007; Schmidtke, Schröder, Jacobs & Conrad, 2014; Soares, Comesana, Pinheiro, Simõnes & Frade, 2012; Võ, Conrad, Kuchinke, Urton, Hofmann & Jacobs, 2009). It is thus likely that manipulations on the valence dimension are confounded with differences in arousal whenever arousal has not been

1 While the words “emotion” and “affect” are sometimes used to relate to different functional aspects – emotion most often being used to describe a psycho-physiological process while affect only relates to the consciously perceived feeling – both terms are used interchangeably within the present manuscript.

explicitly controlled.

The simple two-dimensional model of human emotion was the first theoretical framework that has been tested within the LDT. Hofmann et al. (2009) pioneered in experimentally manipulating valence and arousal independently and simultaneously in a comparison of low arousing positive, low arousing negative, high arousing negative and low arousing neutral words. Their results reconcile data supporting the automatic vigilance and the automatic evaluation hypotheses, showing that low arousing positive and high arousing negative words are both processed faster than low arousing neutral words, while low arousing negative words are processed much slower than all other categories. Interestingly, Hofmann et al. (2009) additionally documented a specific timing for these effects, with arousal affecting the early N1 component of the ERP at about 100ms after stimulus onset, which is also known to be sensitive to the affective conditioning of nonwords (Fritsch & Kuchinke, 2013). Building upon Hofmann et al.'s (2009) initial work, several subsequent studies focused on the specific contributions of valence and arousal, as well as their interaction. Bayer et al. (2011), for example, reported two independent main effects: a slowdown in word recognition speed for negative (when compared to positive) words and a speed-up caused by increased levels of arousal. These results nicely replicated Hofmann et al. (2009). Further support comes from multiple regression analyses on large volume databases, so called mega-studies. For example Larsen et al. (2008) used data on more than 1,000 words provided by the English Lexicon Project (ELP, see Balota et al., 2007) and the Affective Norms for English Words list (ANEW, see Bradley & Lang, 1999) to document facilitative processing for arousal and several highly significant one-, two- and three-way-interactions with valence. These results indicate very complex valence-arousal-interdependencies (see Figure 2 in Larsen et al., 2008), which can be summarized to broadly indicate facilitative processing for increasing levels of arousal and increasing levels of positivity, however.

Although the affective word processing literature seemed to converge in its results since the additional consideration of affective arousal, the conclusions from Larsen et al. (2008) were challenged from different groups using comparable methods almost immediately after publication. Estes & Adelman (2008a) also relied on the ELP and the ANEW norms but showed that the LDRT variance between positive and negative words is much greater than within each (emotional) category, which they interpret as support for the automatic vigilance hypothesis, given that negative words were processed much slower than positive words. Arousal, in their study, did not interact with valence at all. Kousta et al. (2009) added to the discussion by showing that an increased number of neutral words and thus an overall more balanced stimulus set reveals no effect of arousal at all, but rather a generally facilitative effect of emotional valence irrespective of the emotional category. Based on almost 1,500 words, these results again support the automatic evaluation hypothesis. Finally, Recio et al. (2014) further analyzed the nature of valence-arousal interactions in an orthogonal 3 (positive, neutral, negative) x 3 (low, medium, high arousal) experimental design. Independent main effects were reported, mainly driven by facilitated processing for positive and high arousal words, but with a very different effect structure depending on the specific valence-arousal interaction. Low arousal words, for example, were processed as would be expected according to the automatic vigilance hypothesis, while processing speed for positive, negative and neutral words did not differ in the high arousal condition. Moreover, negative words seemed to be more affected by arousal than positive words. Based on these studies, it can be concluded that a simple two-dimensional emotion model without additional assumptions does not reliably explain known affective word processing effects.

Given these inconsistent effects documented in the literature, recent research focused on alternative theoretical models that might account for LDT effects. Based on a framework by Robinson and colleagues (Robinson, Storbeck, Meier & Kirkeby, 2004), for example, the so called approach-withdrawal hypothesis has been applied to affective word recognition research, mainly because it directly addresses the critical valence-arousal-interaction. The core assumption of this model is that stimuli with positive valence elicit approach-related motivational response tendencies, while stimuli with negative valence elicit withdrawal-related behavior, while similarly opposing motivational tendencies are also seen at the arousal dimension: Low arousal is assumed to be associated with approach behavior and high arousal is assumed to elicit withdrawal (also Davidson, 1998). Robinson et al. (2004) proposed that motivational approach and withdrawal tendencies are initiated independently and thus need to be integrated in the process of stimulus evaluation, which is already well studied in other research fields (for a review, see Briesemeister, Tamm, Heine & Jacobs, 2013). Based on Robinson et al.'s (2004) work, it was recently hypothesized that for low arousing positive and high arousing negative words, the approach and withdrawal tendencies are congruent, which leads to overall facilitated processing and thus relatively fast LDT responses, given that no additional processing steps are necessary (Citron, 2011). In case of high arousing positive and low arousing negative words, however, the divergent motivational tendencies cause a cognitive conflict and the difficulties of solving this conflict by integrating both motivational tendencies is proposed to result in slower LDRTs.

The approach-withdrawal hypothesis accounts for most affective LDT effects discussed so far (exceptions: Bayer et al., 2011; Kousta et al., 2009, Recio et al., 2014): It explains, why Hofmann et al. (2009) found high arousing negative words (i.e. avoidance eliciting stimuli) to be processed faster than neutral words, while low arousing negative words (i.e. conflict eliciting stimuli) where processed slower than neutral words and thus accounts for the heterogeneity of results in studies using negatively valenced words (Algom et al., 2004; Carretié et al., 2008; Kanske & Kotz, 2007; Kuchinke et al., 2007; Schacht & Sommer, 2009a; 2009b; Scott et al., 2009). It also explains why low arousing positive words (i.e. approach eliciting stimuli) were processed faster than neutral words in Hofmann et al. (2009) and almost all published affective lexical decision studies. Most important, however, the approach-withdrawal hypothesis predicts that high arousing positive words should be processed slower than low arousing positive words, which was never found and never explicitly tested in previous studies but addressed in a series of recent LDT experiments. Citron, Weekes & Ferstl (2013) presented first marginal evidence in an ERP study, showing that words that elicit conflicting approach-withdrawal motivations (high arousing positive and low arousing negative words) tend to be processed slower and tend to elicit a smaller sustained slow positivity around 700-1,000 ms after stimulus onset than words with congruent orientations. Neither effect did actually reach significance (both $0.1 > p > 0.05$), but in a more recent replication focusing solely on behavioral LDT effects, both effects were significant (Citron, Weekes & Ferstl, 2014). A final replication attempt (Citron, Gray, Critchley, Weekes & Ferstl, 2014) using functional magnetic resonance imaging (fMRI) as additional source of information reports no interaction effects on LDRTs but on word recognition accuracy, where words in conditions with congruent approach-withdrawal motivations were processed more accurate than words in conditions assumed to elicit a conflict. Again, this was in line with the approach-withdrawal hypothesis. The effect was accompanied by a significant interaction within the blood-oxygen level dependent (BOLD) signal recorded from the right insula, extending to the superior temporal gyrus, which the authors interpret as an indicator for the implicit integration of cognitive stimulus evaluation with conflicting approach-withdrawal tendencies.

But even though the approach-withdrawal hypothesis can superficially account for most published behavioral affective word recognition effects, the results are far from being stable (Citron, 2011) and some data are impossible to reconcile with the approach-withdrawal framework. Bayer et al. (2011), for example, reported facilitated, not slowed processing for high arousal positive words, and mega-studies by Kousta et al. (2009) and Vinson, Ponari and Vigliocco (2014) argued that the role of arousal might be overestimated. Recio et al. (2014) additionally showed a strong asymmetry in arousal effects, documenting that arousal affects negatively valenced words stronger than positive words. Thus, even though the approach-withdrawal hypothesis is in accordance with much of the LDRT data, some effects are still surprising.

A Different Perspective: Discrete Emotion Categories

Most affective word recognition research uses manipulations along valence and/or arousal dimensions. But even when focusing on those alone, still some affective word recognition studies report that their results actually are better described when assuming affective *categories*. Estes and Adelman (2008a), for example, argue that the LDRT variances vary stronger between positive and negative words than within each valence category, which they interpret as indicator for categorical processes. A recent study by Scott et al. (2014) further supports this interpretation, showing a frequency*valence interaction for negative words when the affective manipulation is implicit to the task requirements, but no such interaction when it is explicit. Given that effects for positive words remained stable irrespective of the task instructions, the authors suggest that positive and negative word processing might rely on distinct systems rather than a single affective dimension, which is also in line with the valence specific arousal asymmetries from Recio et al. (2014) discussed above.

In fact, the dimensional approach, assuming that all human emotions can be described with a limited number of affective dimensions such as valence and arousal, has repeatedly been challenged by discrete emotions theories. These theories assume the existence of discrete, evolutionary derived emotion categories, with each discrete emotion being characterized by distinct behavioral responses (e.g. Izard, 1990), psychophysiological markers (e.g. Christie & Friedman, 2004) and patterns of neuronal activation (e.g. Vytal & Hamann, 2010). Given the close relationship between language and emotion (Barrett et al., 2007), especially in some discrete emotion theories (Panksepp, 2008), leaving dimensional emotion theories behind to investigate the effects of specific emotion categories on affective word recognition seems like a logical next step. Parrott, Zeichner and Evces (2005), for example, used the LDT to compare the performance of subjects high and low in trait anger on anger-related, happiness-related, sadness-related and neutral words. While no differences were observed for subjects that scored low on the trait anger scale, subjects with high trait anger showed enhanced processing of anger-related words when compared to any other condition. Moreover, happiness related words were processed faster than neutral stimuli. A second study used a similar approach to investigate the influence of experienced disgust on information processing in high versus low contamination phobic subjects (Armstrong, Divack, David, Simmons, Benning & Olatunji, 2009). A LDT with happiness-related, disgust-related, threat-related and neutral words revealed a main effect of emotion category, with disgust words being processed slower than any other condition. While this effect was independent of the mood manipulation, Silva, Montant, Ponz and Ziegler (2012) replicated Armstrong et al.'s (2009) disgust effect, showing that the crucial between-subject variable is not contamination-phobia but disgust sensitivity. Participants scoring high on a standardized disgust sensitivity scale revealed inhibited processing of disgust related words, while participants scoring low on that scale processed disgust words even faster than neutral control words. Neither valence, arousal or empathy accounted for these effects, showing that they are indeed disgust and thus (discrete) emotion specific. A follow-up study by the same group furthermore suggests that this disgust specificity might relate to the anterior insula cortex, which is known to be involved in general disgust processing (Wicker, Keysers, Plailly, Royet, Gallese & Rizzolatti, 2003) and is likely to play a role in the processing of disgust words as well (Ponz et al., 2013a).

Using Affective Word Recognition to Test Discrete Emotion and Affective Dimension Models

While the existing affective word recognition literature, as reviewed above, documents that a) affective information does affect word recognition speed and that b) the LDT can be used to test specific predictions from different theories of emotion, actual direct comparisons of different emotion theories using lexical stimuli remain sparse (e.g. Vinson et al., 2014). The present project is meant to fill this gap. In a series of experiments, the predictive power of the discrete emotion framework was contrasted with the predictions of affective dimension conceptions.

In a first step, as described in detail in chapter 02, normative data on five different discrete emotions for almost 2,000 words was collected. These then served as stimulus material for the subsequent experiments, as also described in the following chapters. Following the mega study approach as described in Estes and Adelman (2008a) and Larsen et al. (2008), multiple regression analyses on data provided by the ELP were used to directly compare the predictive power of discrete emotion variables with the predictive power of valence, arousal and their interactions. The results, derived from a re-analysis of data from the native English sample, were then compared with data collected from a German sample. These studies are described in chapter 03.

The chapters 04 and 05, finally, built upon and extend the previous chapters by incorporating discrete emotion and affective dimension manipulations in a single orthogonal design, additionally adding EEG (chapter 04) and fMRI (chapter 05) to additionally record the associated brain activity. The inclusion of additional dependent variables seemed necessary, given that LDRT sometimes are not sensitive enough to detect differences in the underlying processes. Moreover, even though several affective word processing studies agree that valence effects precede those of arousal in the ERP (Bayer et al., 2012; Recio et al., 2014), the results are inconsistent (e.g. Hofmann et al., 2009; see Citron, 2012 for a review). The same is true for previous neuroimaging results. Table 1.1 gives an overview of results from three fMRI studies that used the LDT to investigate the neural correlates of affective word processing. Even though very different stimulus materials and experimental settings were used in these studies, it seems plausible to assume that at least some consistent results should be expected, given that all three experiments were using manipulations alongside the valence and arousal dimensions.

Unfortunately, there is no consistent overlap in the activation found for positive versus neutral or negative versus neutral words, as is obvious from Table 1.1:

Table 1.1: Direct comparison of fMRI results from studies using the affective LDT

Brain structure	Kuchinke et al., 2005	Nakic et al., 2006	Citron et al., 2014
R inferior frontal g.	neg > neu		
L posterior cingulate g.	*neu > neg* pos > neg	*neg > neu*	
L fusiform + parahippocampal g.	neu > neg		
L parahippocampal g.	*neu > neg*		*HA pos > LA pos* *HA pos > HA neg*
L anterior cingulate g.	neu > neg pos > neg		
R superior + medial frontal g.	neu > neg		
R superior + middle temporal g.	*neu > neg*		*HA pos > HA neg*
R medial frontal g.	neu > neg		
R posterior cingulate g.	neu > neg		
R hippocampus	neu > neg pos > neg		
L orbitofrontal g.	pos > neu		
L middle temporal g.	*pos > neu*	*neg > neu*	
R middle temporal g.		neg > neu	
R superior + middle temporal g.	*pos > neu*		*HA pos + LA neg* *> LA pos + HA neg*
R superior frontal g.	pos > neu		
R middle frontal g.	neu > pos		
R anterior cingulate g.	pos > neg	neg > neu	
L amygdala		neg > neu	
R amygdala		neg > neu	
R superior occipital g.			pos > neu neg > neu
R precuneus			neg > neu
R insula			HA pos + LA neg > LA pos + HA neg HA pos > LA pos
L posterior insula			HA pos + LA neg > LA pos + HA neg HA pos > LA pos
L superior temporal g.			HA pos > LA pos
R Pulvinar			LA neg > HA neg

Note: pos = positive, neu = neutral, neg = negative, HA = high arousal, LA = low arousal

Again, these data clearly demonstrate that no simple explanation is sufficient to explain the diversity in documented LDT effects, neither on a behavioral nor on a psycho-physiological level. The present project thus takes a different approach, introducing a systematic discrete emotion framework into the affective word processing literature[2].

The Panksepp-Jakobson hypothesis

A second reason to justify this change in perspective comes from the Panksepp-Jakobson hypothesis introduced initially by Jacobs et al. (2014). In simple words, the Panksepp-Jakobson hypothesis states that evolution had no time to develop neural networks that specifically underlie art perception, yet alone structures for affective processes in reading. The aesthetic reading process as described by Jakobson and Halle (1969) therefore must be directly linked to the affective networks shared among all mammalian species as investigated by Panksepp (2008). Hence the name.

While the exact functional and neuroanatomical link between emotion and language remains unknown, different papers have provided initial evidence for its existence. In a nicely written review, Newman (2007) summarizes the neural structures underlying the universal infant vocalization of crying, which can be understood as a very early form of primitive, non-symbolic language. He points out the importance of limbic and subcortical brain structures known from emotion research, such as the amygdala and the periaqueductual gray, and he also notes that higher order frontal and prefrontal structures discussed to encode affective valence (e.g. the orbitofrontal cortex, see Wilson-Mendenhall, Barrett, & Barsalou, 2013) are not involved. This is also in line with Panksepp (2008), who argues that language evolved from affective networks and affective vocalizations through a prosodic-affective bridge. Of course, the way from a separation cry to the highly abstract written language representation used in affective word processing experiments is a long one. Still, the connection is there.

Shanahan (2008), for example, suggests that external events that trigger emotional responses also form internal representations of the event, which “then begin to take on “meaning”” (p. 13) and “begin to take on a life of its own, such that the emotional experience eventually becomes *reified*” (p. 13). This reification then provides the basis for later symbolism in the sense that “these images […] become themselves means for perceiving and interpreting the environment” (Shanahan, p. 13).

Taken together, and this is one of the implications from the Panksepp-Jakobson hypothesis, studies which consider emotion and language from an evolutionary/animal

2 Please note: Given that the studies described in chapters 02 to 05, some of the information presented there is repetitive and thus redundant. This is, however, necessary, given that the present dissertation was written as a cumulative dissertation.

research perspective mostly agree that emotions must be operationalized in functionally discrete categories. Affective word processing research on human subjects, however, still focuses almost exclusively on the effects of affective dimensions. The present work aims to broaden the perspective, suggesting that a) discrete emotions are suited to describe affective word processing, and that b) an emotion model derived from animal research (e.g. Panksepp, 1998) can help to understand the neuronal processes underlying affective word processing.

Discrete Emotion Norms for Nouns

Chapter 02

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Abstract

The Berlin Affective Word List (BAWL, Võ, Jacobs, & Conrad, 2006) and the BAWL-R (Võ et al., 2009) are two commonly used lists to investigate affective properties of German words. The two dimensional valence and arousal model of affect underlying the BAWL is traditionally contrasted with models describing affect in discrete emotional categories, which, however, are not currently incorporated in the BAWL. In order to allow future studies to investigate affective processing from both perspectives, or to directly compare them, the present study collected data assigning nouns taken from the BAWL-R to discrete emotion intensities, which in turn allows the assignment to discrete emotion categories. It presents Discrete Emotion Norms for Nouns – Berlin Affective Word List (DENN-BAWL). Using these ratings and the psycholinguistic indexes from the BAWL-R, the DENN-BAWL allows researchers to design experiments using highly controlled and reliable word material. Data have been archived at http://www.fu-berlin.de/allgpsy/DENN-BAWL.

Introduction

Many studies investigating human emotion rely on tasks that require verbal stimulus material. Prominent examples are the emotional Stroop (Dresler, Mériau, Heekeren & van der Meer, 2009; Phaf & Kan, 2007; Thomas, Johnstone & Gonsalvez, 2007), recognition memory test (Grider & Malmberg, 2008; Võ et al. 2008; Zimmermann & Kelley, 2010), the LDT (Kuchinke et al., 2007; Schacht & Sommer, 2009a; Scott et al., 2009), naming (Estes & Adelman, 2008a; Simpson, Snyder, Gusnard & Raichle, 2001), verb generation (e.g. Simpson et al., 2001), or word-stem completion (Danion, Kauffmann-Muller, Grangé, Zimmermann & Greth, 1995). However, because numerous variables are known to influence visual word processing (Graf et al., 2005), well controlled and reliable emotion inducing stimulus material is necessary in order to produce interpretable effects. In most cases, researchers depend on published norm lists, providing reproducible stimulus characteristics.

Studies using English, for example, most often use the ANEW (Bradley & Lang, 1999). ANEW provides norms for 1,034 nouns, verbs and adjectives, characterized among the three affective dimensions of valence -indicating the positivity or negativity of a stimulus, arousal -indicating the excitement, and dominance -indicating the feeling of being in control versus being controlled (Osgood, Suci & Tannenbaum, 1957). All three dimensions have proven to strongly influence human behavior (e.g. Hess, Adams & Kleck, 2005; Larsen et al., 2008; Thomas & Hasher, 2006) and their neural correlates have been examined in several imaging studies (e.g., Anders, Eippert, Weiskopf & Veit, 2008; Lewis, Critchley, Rotshtein & Dolan, 2007; Nielen et al. 2009; Steinmetz & Kensinger, 2009). This three-dimensional affective space model has been reduced to a two-dimensional model in most research lately, relying solely on valence and arousal dimensions (Bradley & Lang, 2000; Russell, 2003).

Affective dimensions are only one way to conceptualize emotion, however. To allow for a more complete view of the matter, supplemental material for the ANEW was recently published. Stevenson, Mikels and James (2007a) implemented discrete emotion norms for happiness, anger, fear, disgust and sadness into the ANEW database based on classic discrete emotion models as originally suggested by Charles Darwin (1872). Discrete emotions are a second major approach to conceptualize the affective space. Recent brain stimulation studies in animals demonstrated emotion specific behavioral responses to stimulation of predefined brain regions, thereby supporting the discrete emotion approach (e.g., Panksepp, 1998, 2006a). Discrete emotion effects have mainly been shown in emotion recognition from facial expressions (Campbell & Burke, 2009; Elfenbein, Beaupré, Lévesque & Hess, 2007; Seidel, Habel, Kirschner, Gur & Derntl, 2010) or static pictures (see Mikels et al., 2005). Some word processing studies document LDRT effects as well (Armstrong et al., 2009; Parrott et al., 2005). These latter studies, however, did not use published discrete emotion norms and concentrated on contamination-phobic subjects (Armstrong et al., 2009) and on subjects with high trait anger (Parrott et al., 2005). Thus, further experimental investigations are needed using combined approaches given that both discrete emotion and dimensional theories share a great overlap in explanational value (Reisenzein, 1994).

Because of ANEW's success, norm lists for emotional words have been collected in non English speaking countries as well. Prominent examples are the Spanish adaption of ANEW (Redondo et al., 2007), the Finish and British English word list (Eilola & Havelka, 2010), and the Berlin Affective Word List (BAWL, see Võ et al., 2006) which was recently revised (BAWL-R, see Võ et al., 2009) and now contains norms on the dimensions valence and arousal for more than 2,900 German words including nouns (2,107), verbs (504), and adjectives (291). Norms for discrete emotions, however, which would allow for a broader focus on emotional word processing in non-English speaking populations, are not yet available in any other language.

Following Stevenson et al. (2007a), this study meant to provide researchers with a list of reliable discrete emotion norms for German nouns, hereafter referred to as the DENN-BAWL. In a first step, the exact same discrete emotion categories to supplement the ANEW, namely happiness, anger, fear, disgust and sadness, were collected to supplement the BAWL.

Brain stimulation studies, which have identified the neurobiological systems eliciting these emotions (namely the PLAY system, the RAGE system, the FEAR system, the DISGUST system and the PANIC system, see Panksepp, 1998, 2006a; Toronchuk & Ellis, 2007a, 2007b), provide strong evidence that at least some discrete emotions are not culture specific (Ekman & Friesen, 1971; Wierzbicka, 1986), but are found universally, even in different mammalian species. Thus, it is believed that the DENN-BAWL would not only allow investigations with German speaking subjects, but may also trigger broader, cross-cultural comparisons, given that norms are available in two languages and given the likely universal neurobiological basis of the discrete emotion effects.

In a second step, this study aimed at demonstrating that the discrete emotion ratings collected with a German speaking population actually could account for substantial variance in behavioral measures of single word processing. The LDT was chosen for this purpose since it is the only verbal stimuli based task that has been shown to be affected by both emotional dimensions (e.g. Kuchinke et al., 2007; Schacht & Sommer, 2009a; Scott et al., 2009) and by discrete emotions alike (Armstrong et al., 2009; Parrott et al., 2005).

When subjects are asked to indicate via button press whether a presented letter string is a correct word (e.g. “TAXI”) or a nonword (e.g. “TAFI”), positive and highly arousing negative stimuli are known to facilitate processing, while low arousing negative stimuli are processed slower than matched neutral words (Hofmann et al., 2009). Concerning discrete emotions, happiness (representing positive valence) and fear dimensions (representing negative valence) were chosen for the LDT.

When comparing LDRTs and ERR to words rated as highly happiness related (highHap condition) with those to words not rated as highly happiness related (lowHap condition), words in the highHap condition were expected to be processed faster than words in the lowHap condition, based on previous findings for dimensional emotion studies (Kuchinke et al., 2007; Schacht & Sommer, 2009a; Scott et al., 2009). Similarly, the processing of words rated as highly related to fear (high fear condition) were compared with the processing of words rated as not highly related to fear (low fear condition). Concerning this manipulation, a precise prediction seems difficult considering that investigations of discrete emotion intensities are rare (Reisenzein, 1994) and inconclusive.

Finding any effect of either fear or happiness intensities on either LDRT or ERR when the stimulus material is controlled for mean valence and arousal norms would document that the collected discrete emotion norms could capture variance that is not captured by the standard scales of valence and arousal alone. Moreover, it would encourage further investigation of discrete emotion effects using the DENN-BAWL.

Rating Methods

Participants

A total of 79 native German subjects (53 female; mean age = 24.3, S.D. = 6.2, range = 18 to 61) recruited via email lists, a notice posted on campus, and in experimental psychology classes at the Freie Universität Berlin participated in this study. They were offered either course credit or five Euros for participation. Some subjects participated voluntarily without recompense.

Material and Procedure

In order to collect discrete emotion norms, all 1,958 nouns with 4-8 letters length from the BAWL-R (Võ et al., 2009) were selected and subdivided into nine lists containing 200 items and one list containing 158 items. Ratings were collected via an internet-based html script running on a public server provided by the Freie Universität Berlin (for a discussion on internet experiments, see Birnbaum & Reips, 2005).

Subjects were first instructed to carefully read the presented word and then indicate on five independent 5-point Likert scales the intensity of the elicited feelings of happiness, anger, fear, sadness and disgust (1 = low intensity, 5 = strong intensity). Each word was presented individually in black uppercase letters (font type Times New Roman, font size 18) on white background. Subjects were able to individually decide when to advance to the next trial by clicking on a button. Word order was randomized for each subject. Participants were explicitly allowed to rate more than one of the ten different stimulus lists, resulting in an average of 2.7 lists rated per subject (S.D. = 2.7, range 1-10). Online ratings were then averaged offline per item and per discrete emotion category using JMP software (version 7, SAS Institute Inc., Cary, NC). Each word received ratings from at least 20 different subjects.

Rating Results

The stimulus list resulting from the rating procedure including the averaged ratings, the respective standard deviations and an assignment of single words to specific discrete emotion categories can be downloaded at http://www.fu-berlin.de/allgpsy/DENN-BAWL. Altogether, 1,104 words received a higher rating in happiness than in any other discrete emotion variable, and thus were labeled as happiness related words in the list (e.g. “SONNE”, engl. “SUN”; see column “BasicEmoCat liberal”). Using the same logic, 384 words were labeled as anger related words (e.g. “ZORN”, engl. “RAGE”), 261 words were fear related (e.g. “LAWINE”, engl. “AVALANCHE”), 125 words received the highest rating in disgust (e.g. “SCHLEIM”, engl. “SLIME”) and 43 words were classified as sadness related (e.g. “ABSCHIED”, engl. “PARTING”). Additionally, a more conservative classification criterion was applied, assigning words to a specific discrete emotion category only in cases where the averaged rating in one discrete emotion was more than one standard deviation higher than in any other discrete emotion (see column “BasicEmoCat conservative”).

Table 2.1: Correlational analyses for discrete emotions, valence (Val) and arousal (Arou), including descriptive statistics

	Hap	Ang	Sad	Fea	Dis	Val	Arou	Mean	SD	Range
Happiness	1					.839	-.338	2.05	0.83	1–4.48
Anger	-.517	1				-.718	.587	1.65	0.63	1–4.30
Sadness	-.270	0.56	1			-.498	.451	1.38	0.44	1–3.90
Fear	-.417	.617	.699	1		-.636	.679	1.61	0.60	1–3.84
Disgust	-.333	.356	.305	.395	1	-.445	.298	1.38	0.47	1–4.10

Note: Maximum range is 1 – 5. Val and Arou were taken from the BAWL-R. All correlations were significant at the 0.01 level (2-tailed). *Hap* = happiness, *Sad* = sadness, *Fea* = fear, *Dis* = disgust

Correlational analyses with the discrete emotion ratings and the valence and arousal scores taken from the BAWL-R revealed a highly significant positive relationship between happiness ratings and valence, as well as between the four negative discrete emotions and arousal. A negative correlation was found between happiness and arousal, happiness and the other discrete emotion variables, and between the negative discrete emotions and valence. Correlations and some descriptive statistics describing the rating data can be found in Table 2.1.

Lexical Decision Task Methods

Participants

An additional 20 native German subjects (14 female; 18 right handed; mean age = 24.4, S.D. = 4.0, range = 19 to 36) recruited at the Freie Universität Berlin participated in this study. Some of them received course credit for participation, others participated without recompense.

Materials

Stimulus material consisted of 175 nouns taken from the ratings described above and an equal number of nonwords, as described below. Within the word set, five conditions (high and lowHap, neutral, high and low fear) were constructed, each containing 35 items of 4-6 letters in length. Neutral words had valence ratings lying between -0.5 and +0.5 according to the BAWL-R. Negative words (high and low fear conditions) had a valence rating below -1 and positive words (highHap and lowHap conditions) a valence rating above 1. All three valence conditions were matched on number of letters, syllables, phonemes, orthographical neighbors, frequency and averaged bigram frequency using an ANOVA ($p > 0.1$). Estimates were taken from the BAWL-R.

Table 2.2: Mean stimulus characteristics

	Val	Arou	Imag	Length	Phon	Syl	Freq	N	BIG
high fear	-1.71	3.72	4.16	5.03	4.51	1.74	28.48	2.46	185,383
low fear	-1.64	3.63	3.89	5.17	4.66	1.83	20.14	2.09	208,153
neutral	0.07	2.32	4.42	5.26	4.71	1.94	21.94	2.46	172,792
highHap	1.31	2.28	5.06	5.03	4.54	1.77	43.45	2.49	211,117
lowHap	1.25	2.23	4.89	5.14	4.66	1.83	44.17	3.09	223,337

Note: Emotional valence (Val), arousal (Arou), length, phoneme (Phon), syllable (Syl), frequency (Freq), orthographical neighborhood size (N) and bigram frequency (BIG) statistics were taken from the BAWL-R.

Positive and negative categories were split in non-overlapping halves. High fear condition stimuli had a fear score above 2.6 (mean fear = 2.92) and were matched to low fear stimuli (fear score below 2.6, mean = 2.16) on valence, arousal, happiness, sadness, anger, disgust, frequency, imageability, bigram frequency, number of letters, syllables, phonemes and orthographical neighbors using a t-test (all $t < 1$, all $p > 0.3$). Both conditions significantly differed in fear ($t(63.6) = -12.588$, $p < 0.001$). HighHap stimuli had happiness scores above 2.6 (mean happiness = 3.24) and were matched to lowHap stimuli (happiness score below 2.6, mean = 2.19) on valence, arousal, fear, sadness, anger, disgust, frequency, imageability, bigram frequency, number of letters, syllables, phonemes and orthographical neighbors using a t-test (all $t < 1$, all $p > 0.3$). Both conditions significantly differed in happiness ($t(59.7) > -14.315$, $p < 0.001$). Discrete emotion ratings were taken from the online rating described above; all other estimates were taken from the BAWL-R. An overview of the stimulus characteristics is given in Table 2.2.

Nonwords were created by taking an additional 175 words of 4-6 letters length from the BAWL-R and replacing one or two letters, vowels with vowels and consonants with consonants, thus creating pronounceable but meaningless letter strings. They did not differ from words in length and number of syllables in a t-test (all $t < 1$, all $p > 0.3$).

Procedure

Participants sat in a quiet room in front of a 15 inch laptop screen. They were instructed to decide as fast and as accurately as possible whether they were presented a correct German word or a nonword. Decisions were made using left and right index fingers, lying on the respective SHIFT buttons. The button-to-response assignment was counterbalanced across subjects. After nine practice trials, not belonging to the stimulus set and therefore excluded from any analysis, the experimenter left the room provided that subjects did not have further questions.

Stimuli were presented by Presentation 9.9 software (Neurobehavioral Systems Inc., Canada) in randomized trial order in the center of the screen, using black uppercase letters (font type “Arial”, size 24, ~ 0.57° vertical visual angle) on a blank white screen. Each trial began with a fixation cross (+) presented for 500ms in the center of the screen, followed by the stimulus (500ms) at the exact same position and another fixation cross, presented until the button press. Then, the next trial began.

Data preparation

Error-free mean LDRTs were calculated for each condition and each participant. Trials with responses faster or slower than the individual mean LDRT ±2 S.D. were excluded as outliers (5.5%). For error analyses, behavioral errors were summed up per participant and condition. One subject was excluded from all analyses, having committed 38% behavioral errors. The remaining subjects committed 6.5% errors on average. All analyses were computed using SPSS software (version 13.0, SPSS Ins., USA) at an a-priori significance level of 0.05.

Lexical Decision Task Results

The results are summarized in Figure 2.1. A repeated measures ANOVA over all five conditions (high fear, low fear, neutral, highHap, lowHap) revealed a significant main effect in LDRTs [$F(4,72) = 3.766$, $p = 0.008$, partial eta squared = 0.173]. Planned pairwise comparisons using matched pairs t-tests revealed faster responses to words in the highHap condition (mean = 681 ms, SD = 142 ms) when compared to the lowHap condition (mean = 699 ms, SD = 145 ms; $t(18) = -2.272$, $p = 0.036$), to neutral words (mean = 707 ms, SD = 137 ms; $t(18) = -3.248$, $p = 0.004$) and to both fear conditions (high fear: mean = 702 ms, SD = 141 ms; $t(18) = -3.989$, $p = 0.001$; low fear: mean = 699 ms, SD = 132 ms; $t(18) = -3.015$, $p = 0.007$). High and low fear conditions, however, did not differ from each other or from neutral words in LDRT ($p > 0.05$).

Analyzing the ERR, a repeated measures ANOVA over all five conditions (high fear, low fear, neutral, highHap, lowHap) also revealed a significant main effect [$F(72,15) = 7.444$, $p < 0.001$, partial eta squared = 0.293]. Planned pairwise comparisons using matched pairs t-tests revealed more errors in the low fear condition (mean ERR = 3.6, SD = 2.1) when compared to the high fear condition (mean ERR = 2.3, SD = 1.7; $t(18) = 4.301$, $p < 0.001$), to the lowHap condition (mean ERR = 2.2, SD = 2.2; $t(18) = 3.369$, $p = 0.003$), and to the highHap condition (mean ERR = 1.5, SD = 1.4; $t(18) = 5.128$, $p < 0.001$). Additionally, neutral words (mean ERR = 3.2, SD = 1.6) were processed with fewer errors than high fear ($t(18) = 2.178$, $p = 0.043$), highHap ($t(18) = 3.580$, $p = 0.002$), and lowHap words ($t(18) = 2.109$, $p = 0.049$).

Discussion

A lot of research on emotions has been done using lexical stimuli in the past, relying on the two- or three-dimensional affective space model (e.g. Bradley & Lang, 2000; Russell, 2003) and the norms provided by the ANEW (Bradley & Lang, 1999) or the BAWL (Võ et al, 2006). In order to investigate discrete emotion effects on single word processing, however, researchers had to collect stimulus data on their own, since discrete emotion norms were not available (Armstrong et al., 2009; Parrott et al., 2005). This changed with the publication of supplementing norms for ANEW (Stevenson et al., 2007a). Unlike dimensional norms, which are also available in Spanish (Redondo et al., 2007), Finish and British English (Eilola & Havelka, 2010) and German (Võ et al., 2006, 2009), currently discrete emotion norms are only available in English. The purpose of the present study was to amend this by providing discrete emotion norms to German nouns. Moreover, a LDT was used to document the usefulness of the collected norms and to experimentally investigate the influence of different fear and happiness intensities on LDRT and ERR.

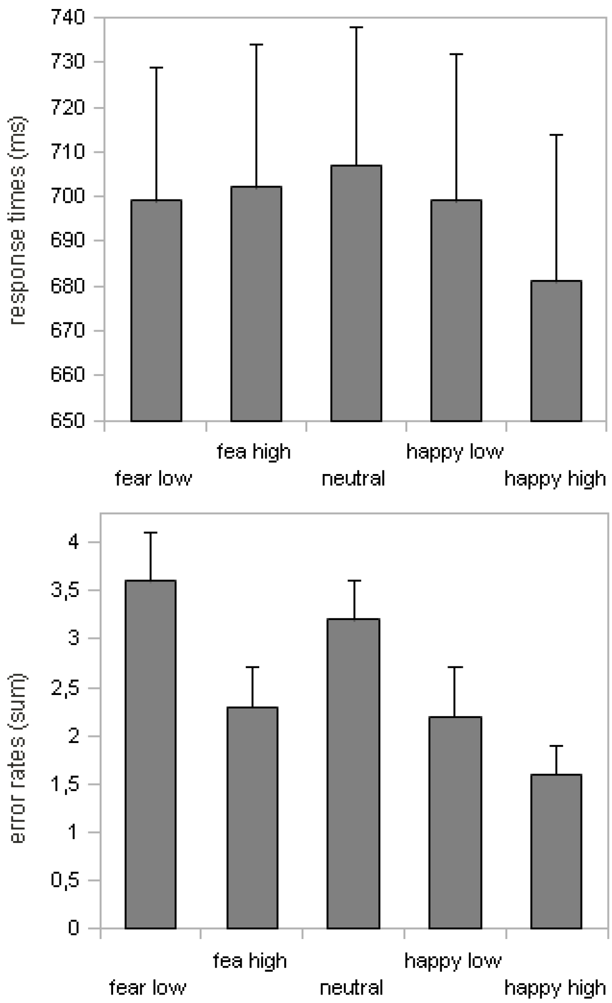

Figure 2.1: Response times (in ms, upper part of the figure) and mean sum of errors for the lexical decision task. Error bars indicate the respective standard errors.

The complete DENN-BAWL, containing almost 2,000 German nouns of 4-8 letters length, can be downloaded from http://www.fu-berlin.de/allgpsy/DENN-BAWL. Descriptive statistics and bivariate correlations between the discrete emotion norms for happiness, anger, fear, disgust and sadness are presented in Table 2.1. The bivariate correlations between the discrete emotion norms and valence resp. arousal norms taken from the BAWL-R replicate previous findings by Stevenson et al. (2007a). Interestingly, the present data further reveal a negative correlation between

German happiness and arousal norms, which was not observed for English norms. Whether this finding is related to increased statistical power in the present study due to an increased stimulus set or whether it reflects crosscultural differences in emotional language processing (e.g. Redondo et al., 2007) could not be answered from the current results but reveals an interesting question that should be addressed in future studies.

In addition to providing discrete emotion norms, the present study also demonstrates that discrete emotion variables account for significant variance in human LDT performance. Investigating the effects of happiness and fear intensity, both, LDRT and ERR were affected (see Figure 2.1), despite the fact that the stimulus material was controlled for the emotional valence and arousal as given by the BAWL-R norms (see Table 2.2). Specifically, highHap stimuli were correctly recognized significantly faster than words in any other condition including lowHap words, which differed from highHap stimuli only in their mean happiness score. This acceleration in lexical processing occurs when stimuli are manipulated on positive valence (Kuchinke et al., 2007; Schacht & Sommer, 2009a; Scott et al., 2009), which, in this study, was controlled between highHap and lowHap stimuli. Thus, facilitated processing is related to happiness even beyond the normative measures of positive valence.

The second manipulation concerning fear intensity did not affect LDRT, but was found to affect ERR in contrast to the initial hypotheses. Negative valence per se has been reported to either facilitate lexical decisions (e.g. Nakic, Smith, Busis, Vythilingam & Blair, 2006), or when controlled for arousal measures, to slow down LDRTs. In the present study, high and low fear stimuli were controlled for both valence and arousal measures which may explain the missing effect in the LDRTs. However, an effect in the errors was still observed.

Possibly, the rather moderate manipulation on fear intensities may have also contributed to this effect. High fear and low fear conditions, although non overlapping, differed in fear intensity only 0.72 points. Future studies are needed to investigate whether the reported relationship between fear intensity and LDRT is mediated by arousal, as indicated by this study.

Despite the missing LDRT effect, fear intensity variation significantly influenced lexical decision accuracy. Subjects committed significantly fewer errors when presented with words in the high fear condition than when presented with the low fear condition words. Just as with the happiness intensity effect, this difference in ERR indicates that discrete emotion intensities influence single word processing beyond the previously discussed effects of the dimensional affective space accounts. Previous papers proposed that emotion related effects in single word processing are caused by automatic evaluation (Murphy & Zajonc, 1993; Pratto & John, 1991), interfering with the actual task. Additionally, language is thought to be of special importance, since it is supposed to serve as a context for emotion perception (Barrett, Lindquist & Gendron, 2007). The ERR effect for fear intensity manipulations and even more the LDRT effect for happiness intensity manipulations presented in this study are in line with the automatic evaluation approaches (Murphy & Zajonc, 1993; Pratto & John, 1991), documenting that discrete emotions, just like affective space dimensions, affect lexical processing even when the affective information is irrelevant for the processing of the task. Accordingly, contextual learning proposed by Barrett et al. (2007) seems to be more emotion specific than previously considered in the word processing literature, where dimensional theories are dominating. Finally, since these results were achieved despite the control for valence and arousal variables, this study documents the additional predictive power of discrete emotions, and in particular the DENN-BAWL norms, over and above emotional dimensions as suggested by Stevenson et al. (2011).

Future Uses

The DENN-BAWL was collected to allow for a broader perspective when investigating emotion effects with verbal stimuli in the German language. Thanks to the BAWL and the BAWL-R, main effects of valence and arousal on word processing as well as their interactions are well documented (Hofmann et al., 2009; Kuchinke et al., 2007), and some of their associated electrophysiological and neuroanatomical correlates have been investigated (Hofmann et al., 2009; Kuchinke et al., 2005). As can be seen from the present study, the two-dimensional approach may be challenged when investigating discrete emotion categories.

In providing the DENN-BAWL to other researchers in the field, it is hoped that discrete emotions will be investigated systematically to increase knowledge of discrete emotion effects in single word processing. Still, several questions remain unanswered. Do fear related responses, which from an evolutionary perspective should lead to withdrawal behavior, behaviorally differ from anger related responses? Are happiness and sadness indeed antagonistic emotions as folk theory suggests? The supplements for ANEW and the DENN-BAWL enable researchers to investigate such questions, and they allow the transfer of knowledge to other cognitive domains such as recognition memory.

In addition to questions focusing on discrete emotions alone, combined studies are possible investigating the potential interdependencies of both dimensional and discrete emotion approaches. How do discrete emotion intensities affect LDT performance when valence and arousal are controlled? This study provides the first evidence in favor of discrete emotion effects for happiness and fear, which leads to speculation about similar emotion specific effects for anger, disgust or sadness, as well as interactions between them.

The DENN-BAWL hopefully helps to answer at least some of these questions and to successfully stimulate further research on emotion.

Discrete Emotion Effects

Chapter 03

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Abstract

Our knowledge about affective processes, especially concerning effects on cognitive demands like word processing, is increasing steadily. Several studies consistently document valence and arousal effects, and although there is some debate on possible interactions and different notions of valence, broad agreement on a two dimensional model of affective space has been achieved. Alternative models like the discrete emotion theory have received little interest in word recognition research so far. Using backward elimination and multiple regression analyses, we show that five discrete emotions (i.e., happiness, disgust, fear, anger and sadness) explain as much variance as two published dimensional models assuming continuous or categorical valence, with the variables happiness, disgust and fear significantly contributing to this account. Moreover, these effects even persist in an experiment with discrete emotion conditions when the stimuli are controlled for emotional valence and arousal levels. We interpret this result as evidence for discrete emotion effects in visual word recognition that cannot be explained by the two dimensional affective space account.

Experiment 1

Introduction

Single word recognition, that is the mechanisms of identifying the meaning of a written or spoken word, is standardly investigated by means of the LDT, where participants judge the lexical status of a presented letter string on whether it is a correct word (e.g. 'PAPER'), or not (pseudo- or nonwords, e.g. 'PAPET'). Given that cognitive and affective processes highly interact, it is not surprising that psycholinguistic research revealed effects of affective variables in word recognition by manipulating the emotionality of the presented words (Hofmann et al., 2009; Kanske & Kotz, 2007; Kousta et al., 2009; Kuchinke et al., 2005, 2007; Larsen et al., 2008; Nakic et al., 2006; Schacht & Sommer, 2009a; Scott et al., 2009). These experimental manipulations are often operationalized along the two dimensions of the affective space, namely emotional valence, which indicates whether a stimulus is positive or negative, and emotional arousal, which describes the emotional intensity associated with the stimulus that can be linked to physiological activation (Bradley & Lang, 1999, 2000; Russell, 2003; Wundt, 1896).

Both, effects of emotional valence and arousal on word processing are well documented. While positive valence is known to facilitate lexical processing in the LDT (Kanske & Kotz, 2007; Kuchinke et al., 2005, 2007; Schacht & Sommer, 2009a; Scott et al., 2009), a facilitatory effect for negatively valenced words is observed only at high levels of emotional arousal (Hofmann et al., 2009; Kanske & Kotz, 2007; Larsen et al., 2008; Nakic et al., 2006). At low arousal levels, negative stimuli are sometimes processed even slower than comparable neutral words (Hofmann et al., 2009; Larsen et al., 2008).

Concerning the valence effects, two theoretically distinct explanations dominate the literature on emotional word recognition. A first explanation is based on the view that emotions emerge from two underlying motivational systems, appetitive and aversive (Kousta et al., 2009; Lang, 1995; Lang, Bradley & Cuthbert, 1990). According to this view, highly valenced stimuli lead to faster approach or avoidance responses than less valenced stimuli and therefore to differences in processing speed. Valence is considered a continuous dimension in these approaches, with a stepless transition from the positive to the negative pole and a neutral midpoint. Estes and Adelman (2008a, 2008b), in contrast, derived their categorical valence conception from the automatic vigilance (Pratto & John, 1991) and automatic affective evaluation (Murphy & Zajonc, 1993) models, which state that all stimuli are evaluated automatically on their affective value as either being positive (appetitive) or negative (aversive). In this conception, emotional stimuli vary more between the affective categories than within (Estes & Adelman, 2008b). According to Estes and Adelman a further differentiation within the positive category and within the negative category is not reasonable. Both theories are supported by experimental evidence (for continuous valence, see Kousta et a., 2009; Larsen et al., 2008; for categorical valence, see Estes & Adelman, 2008a, 2008b; Etcoff & Magee, 1992; Laukka, 2005; Young, Rowland, Calder & Etcoff, 1997).

As a consequence, Estes and Adelman correctly predict that response times in visual word recognition vary with emotional categories, but not as a function of emotional intensity within the positive or negative category (Estes & Adelman, 2008a, 2008b). Moreover, they are able to show that their model explains a comparable amount of variance as the continuous model (Larsen et al., 2008) in a multiple regression analysis on lexical decision performance data, while being more parsimonious in terms of the models' explanatory value due to five fewer explanatory variables. Still, criticism was raised regarding the appropriateness of the database used in Estes & Adelman (2008a, 2008b). Kousta et al. (2009) discussed that the valence norms in Estes & Adelman are not normally distributed which might bias the results of the regression analyses reported therein, and that the amount of neutral words was underrepresented in this study. Accordingly, relying on a larger corpus with more neutral stimuli Kousta et al. (2009) again found evidence in support of the continuous valence conception (but didn't directly contrast the two accounts).

Models relying on emotional valence and arousal are the most dominant models in the literature on emotional processing, but they are not without alternatives. From an evolutionary view, it is often assumed that human emotions are categorized in terms of discrete emotions (Darwin, 1872; Ekman, 1992; Ekman, Friesen & Ellsworth, 1972; Panksepp, 1998). Unlike the continuous valence model, discrete emotion theories suggest discrete emotion categories. And unlike the categorical valence model, it is suggested that both, positive and negative valence category are further differentiated. At least five different discrete emotion categories – happiness, sadness, anger, fear, disgust – can be identified from facial or vocal expression. This ability to discriminate biologically significant expressions is discussed as an inborn ability and has been shown to generalize across different human cultures. Besides their origin in biological markers, discrete emotions are also elicited by other types of ecological valid stimuli, such as film clips (Hewig et al., 2005; Kreibig, Wilhelm, Roth & Gross, 2007), complex pictures (Britton et al., 2006) and verbal descriptions (Burnett, Bird, Moll, Frith & Blakemore, 2009; Barrett et al., 2007; Reisenzein, 1994).

An evolutionary explanation is not plausible for these stimulus types, but contextual learning has been suggested as a key process in linking such stimulus material to discrete emotions (Barrett et al., 2007). Emotion categories acquired during childhood may facilitate the perception of discrete emotions in different circumstances, a mechanism that is most probably moderated by the use of language (Barrett et al., 2007) which itself is known to be closely linked to phylogenetically old brain systems responsible for emotional processes (Panksepp, 2008). Accordingly, it seems plausible to assume that single word stimuli are also linked to discrete emotion categories. First evidence already documents that discrete emotion data affect lexical decision performance in clinical (Armstrong et al., 2009; Parrott et al., 2005) and non-clinical populations (Briesemeister et al., 2011a).

The present study was designed to further examine the role of discrete emotion categories in visual word recognition and to contrast these data with the predictions of continuous and categorical models of the affective space. In the first step, an automatic selection procedure was computed to reveal the best predicting affective variables for LDRTs derived from a large corpus of lexical decision data. These were then validated using multiple regression analyses in a second step. Analyses were computed using the ANEW database (Bradley & Lang, 1999) and the ANEW discrete emotion extension by Stevenson et al. (2007a) to predict normative lexical decision human performance data provided by the ELP (Balota et al., 2007). The ANEW contains normative valence and arousal rating data for more than 1000 English words, which has been extended to also account for normative discrete emotion rating data for happy, anger, sad, fear and disgust discrete emotion categories by Stevenson et al. (2007a). The ELP was chosen as the dependent variable because it contains lexical decision performances from more than 800 subjects on more than 40.000 words. This data was collected across six universities, and has become a standard tool for the investigation of lexical processing (Estes & Adelman, 2008a, 2008b; Larsen et al., 2008), thus allowing for a maximum reproducibility. The results of our analyses suggest that discrete emotion information has a comparable or even enhanced explanatory value as the continuous and the categorical model. To further verify these results on independent data and to overcome the problems of the ANEW database (Kousta et al., 2009), a final lexical decision experiment comprising a factorial variation of discrete emotion content while controlling for effects of valence and arousal was conducted to replicate the multiple regression results.

Backward elimination

Automatic selection procedures are a good possibility to statistically explore which predictors explain most variance in a dependent variable (for details, see Agresti & Finlay, 1997). Reisenzein (1994) documented a close relationship between discrete emotion labels and the dimensional affective space model by showing that discrete emotion words show stable patterns across different intensities along the valence-arousal dimensions. Thus, all three models, the continuous valence model, the categorical valence model and the discrete emotion model, are likely to share considerable variance, which can cause the problem of multicollinearity. Automatic selection procedures in multiple regression analyses avoid multicollinearity, and help to identify the variables that individually account for a significant amount of variance.

Searching for the most promising predictors, we presented affective variables from all three models to the automatic selection procedure, together with other psycholinguistic predictors known to affect lexical decisions (e.g., stimulus length and frequency, see (Graf et al., 2005; Kousta et al., 2009; Larsen et al., 2008), using the average lexical decision times taken from the ELP as the dependent variable. Because of the very univocal literature, valence and arousal were expected to explain reliable variance in the human performance data. Finding discrete emotion variables among the selected variables would, however, strongly support the hypothesis of discrete emotion influences on single word processing.

Materials and Methods

To obtain a data set for the subsequent regression analyses, we followed the procedure described by Estes and Adelman (2008a, 2008b) and Larsen et al. (2008). Stimulus data from ANEW (Bradley et al., 1999) was merged with LDRTs collected from the ELP (Balota et al., 2007). The ELP has collected the performance data in a standardized lexical decision implementation: 40,481 words and 40,481 nonwords were presented to 816 native English subjects in uppercase QBASIC font letters. Each trial began with the presentation of three asterisks for 250 ms, followed by a 50 ms tone and a blank screen for 250 ms. Stimuli remained on screen until button press or for 4 seconds, whichever occurred first. The next trial started after a fixed inter-stimulus-interval of 1,000 ms, and behavioral errors were reported back to the subject.

In addition to the ELP and ANEW data, we added English discrete emotion norms to the data set, collected and published by Stevenson et al. (2007a) for the ANEW. This resulted in a list of 1.023 words. A total of 14 variables was used for backward elimination, namely the psycholinguistic variables logarithm of HAL frequency (Lund & Burgess, 1996), stimulus length (New et al., 2006), orthographic neighborhood size (Andrews, 1997; Grainger & Jacobs, 1996; Holcomb, Grainger & O'Rourke, 2002), syllables, mean bigram frequency (Hofmann, Stenneken, Conrad & Jacobs, 2007), plus the following affective variables: The continuous model variables' continuous valence, arousal and their first-order interaction, the categorical model variable categorical valence, with ANEW valence greater than 5 assigned to positive and ANEW valence smaller than 5 assigned to negative category (definition taken from Estes & Adelman, 2008a; the word 'TAXI', having ANEW valence of 5, was excluded, leaving 1022 words for analysis), and the discrete emotion variables happiness, anger, fear, disgust and sadness (Stevenson et al., 2007a). All variables were centered, and entered in a second step into a multiple regression analysis, using RT as the dependent variable. A backward elimination procedure was applied using SPSS software (version 13.0, SPSS Inc., USA), with standard p-to-leave of 0.1.

Results

An overview of the selection results including the estimated betas is given in Table 3.1. Six variables survived the backward elimination procedure, among them the three discrete emotions variables happiness, fear and disgust. No other affective variable survived. The valence*arousal interaction was eliminated as first affective predictor at second position, categorical valence as last (see Table 3.1). As expected, frequency and length were the best predictors.

Table 3.1: Backward elimination results

Step	Variable	beta	t-value	p-value
1. removal	bigram frequency	-0.002	-0.067	0.947
2. removal	valence*arousal	-0.003	-0.106	0.915
3. removal	anger	-0.007	-0.148	0.880
4. removal	sadness	-0.014	-0.305	0.760
5. removal	arousal	-0.026	-0.888	0.375
6. removal	N	0.031	1.082	0.280
7. removal	dimensional valence	0.084	1.087	0.200
8. removal	categorical valence	-0.055	-1.138	0.188
9. final model	log HAL frequency	-0.469	-18.791	< 0.001
	length	0.261	7.565	< 0.001
	syllables	0.131	3.950	< 0.001
	happiness	-0.091	-2.983	0.003
	disgust	0.089	2.948	0.003
	fear	-0.083	-2.721	0.007

Note: N = orthographic neighborhood size

Experiment 2

The automatic selection results show a consistent picture in favor of a discrete emotion explanation of lexical decision times. Neither continuous valence, as expected according to Larsen et al. (2008) or Kousta et al. (2009) for example, nor categorical valence as expected according to Estes and Adelman (2008a, 2008b), nor emotional arousal or the valence*arousal interaction were identified as predictive affective variables, but three out of five discrete emotion variables, suggesting that happiness, fear and disgust explain significant variance in human RTs. This analysis clearly documents that discrete emotions predict word processing performance in healthy subjects (Briesemeister et al., 2011a).

Still, these results should be interpreted with caution. Automatic selection procedures select the variables that individually account for most variance, but they do not necessarily identify the best theoretically reasonable model. A final conclusion concerning the predictive power of the three emotion models discussed above is not possible on the basis of this analysis alone. In fact, it is quite likely that dimensional models, which claim to account for the entire affective space (Reisenzein, 1994), perform much better than a model including only a limited number of discrete emotions, each of which is by definition limited in explanatory value.

To directly compare the predictive power of the continuous valence model as published by Larsen et al. (2008) and the categorical model published by Estes and Adelman (2008a) with a model including five discrete emotions (i.e., happiness, anger, fear, disgust and sadness), a multiple regression analysis was conducted. Again, best overall performance would be expected from the categorical model (Estes & Adelman, 2008a, 2008b) or the continuous model (Kousta et al., 2009; Larsen et al., 2008), considering the literature. Given the automatic selection results and the behavioral relevance of discrete emotions, however, we expected the discrete emotion model to perform at least comparably well.

Materials and Methods

Again, the ELP, the ANEW and the discrete emotion data from Stevenson et al. (2007a) were merged. All three models were used to predict standardized LDRTs with centered variables, following Larsen et al. (2008). As suggested in Larsen et al. (2008), the continuous model contained the predictors length, log HAL frequency, orthographic neighborhood size, syllables, valence, arousal, squared valence, valence by arousal interaction, cubed valence, squared valence by arousal interaction and cubed valence by arousal interaction. The categorical model, following Estes and Adelman (2008a), predicted LDRTs with the variables length, log HAL frequency, orthographic neighborhood size, syllables, arousal and categorical valence. Contextual diversity was included, which however does not significantly affect overall performance of the regression model as published by Estes and Adelman (2008a). Finally, in the discrete emotion model, length, log HAL frequency, orthographic neighborhood size, syllables, and the five discrete emotion variables happiness, anger, fear, disgust and sadness were used to predict LDRTs. Except for the affective variables, all three regressions used the same predictors. Although the original continuous model from Larsen et al. (2008) did not contain syllables as predictor, it was added in this analysis to ease interpretation of the results. Linear multiple regressions were calculated using SPSS software, level of significance was set to 0.05.

Results

The continuous regression model altogether accounted for 59.0% of the variance (adjusted R square), with length, log HAL frequency, syllables, valence, valence by arousal interaction, cubed valence and cubed valence by arousal interaction as significant predictors. Overall model performance differs from Larsen et al. (2008) because we did not use hierarchical regression analysis, which overestimates predictive power. The categorical regression model explained a total of 58.7% variance (adjusted R square) with length, log HAL frequency, syllables, categorical valence and arousal as significant predictors. The discrete emotion model, finally, with significant predictors length, log HAL frequency, syllables, happiness, fear and disgust, accounted for 59.6% variance in LDRTs (adjusted R square). All three models are summarized in Table 3.2.

Table 3.2: Comparison of three affective regression models

Variable	Categorical model			Continuous model			Discrete emotion model		
	beta	t-value	p-value	beta	t-value	p-value	beta	t-value	p-value
Log HAL	-0.505	-21.477	< 0.001	-0.501	-21.408	< 0.001	-0.482	-20.423	< 0.001
Length	0.294	8.308	< 0.001	0.301	8.525	< 0.001	0.316	8.983	< 0.001
Syllables	0.131	4.129	< 0.001	0.125	3.961	< 0.001	0.131	4.160	< 0.001
N	0.041	1.475	0.140	0.043	1.555	0.120	0.045	1.661	0.1
Val (cat)	-0.101	-4.650	< 0.001						
arous	-0.046	-2.207	0.028	-0.009	-0.250	0.802			
Val (con)				-0.201	-3.820	< 0.001			
Val*arous				0.197	3.496	< 0.001			
Val^2				-0.028	-1.079	0.281			
Val^2*arous				-0.020	-0.581	0.561			
Val^3				0.127	2.156	0.031			
Val^3*arous				-0.190	-3.066	0.002			
Happiness							-0.114	-3.818	< 0.001
Disgust							0.137	4.542	< 0.001
Fear							-0.075	-2.018	0.044
Sadness							-0.025	-0.658	0.511
Anger							-0.046	-1.185	0.236
Adj. R^2	0.587			0.590			0.596		

Note: Log HAL = logarithm of HAL frequency, N = orthographical neighborhood size, Val (cat) = categorical valence, Val (con)/Val = continuous valence, arous = arousal

Discussion

Three affective variables signaling the amount of happiness, fear and disgust significantly predict lexical decision LDRTs according to the automatic selection procedure. When comparing the overall performance of a regression model with five discrete emotion variables with those of categorical and continuous models discussed in the literature (Estes & Adelman, 2008a; Larsen et al., 2008), all three perform more or less equally well. This is not trivial, since dimensional models often claim to account for the entire affective space, while discrete emotions, by definition, are more specific (Izard, 2007). The multiple regression analysis, however, documents that five discrete emotions explain just as much (or even slightly more) variance as both, the dimensional and the categorical model.

The overall LDRT pattern known from the experimental visual word recognition literature was replicated (Hofmann et al., 2009; Kuchinke et al., 2005, 2007; Nakic et al., 2006). Positive valence is consistently accompanied by faster LDRTs, whereas negative words show indifferent results with sometimes increased and sometimes decreased LDRTs as compared to neutral words (Hofmann et al., 2009; Kuchinke et al., 2007). According to the above regression analyses, negative betas for valence and arousal indicate that the dimensional and the categorical model both predict that positive stimuli are processed faster than negative stimuli and that high arousal facilitates processing. The dimensional and the categorical model only differ in their expectations for within valence effects, which is discussed excellently and in great detail in Estes and Adelman (2008b).

Concerning discrete emotions, the regression model predicts faster LDRTs with increasing values of happiness and fear, and slower LDRTs when disgust levels increase. Happiness related words (i.e., positive words) are predicted to elicit faster LDRTs, whereas negative words would show indifferent results depending on the proportion of fear and disgust-related words in the stimulus set. Following the predictions of the discrete emotion model, the proportions of the different negatively valenced discrete emotion words in a given data set explain the indifferent results regarding negative words. So far, the two dimensional affective space models and the discrete emotion model basically predict the LDRT pattern. Considering the bivariate relationships between the valence and arousal norms from the ANEW database and the discrete emotion norms, there is an interesting and crucial difference between the models, however. According to Stevenson, Mikels and James (2007b) and as visible in Figure 3.1, all discrete emotion variables are positively related to emotional arousal, even disgust. Higher levels of disgust are therefore related not only to higher negativity, but also to higher arousal (see Figure 3.1 and Stevenson et al., 2007b). This can explain why arousal did not account for a significant proportion of LDRT variance under the discrete emotion model. Moreover it challenges the two dimensional approaches which both predict that highly arousing negative stimuli are processed faster instead of being processed more slowly, as expected from the discrete emotion models' regression data.

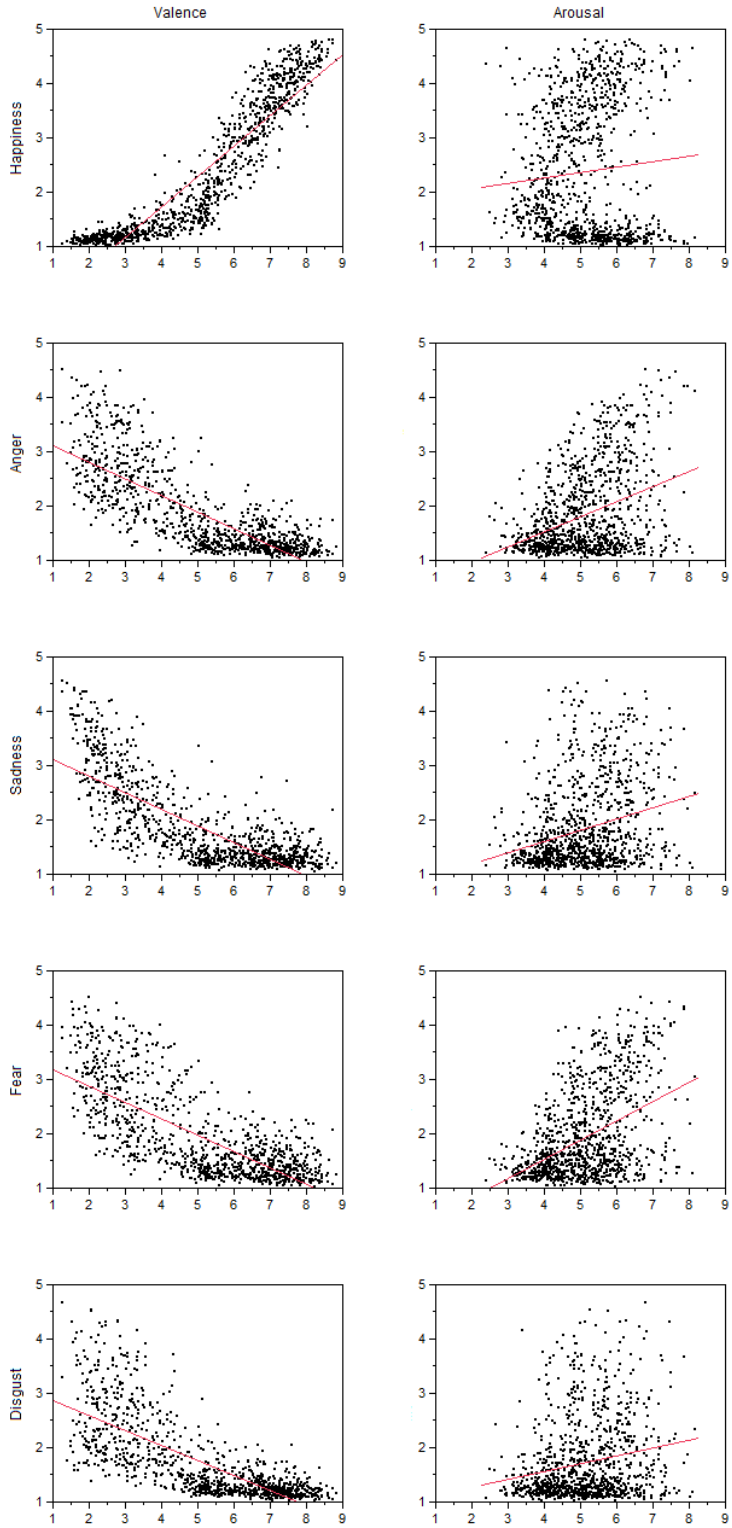

Figure 3.1: The relationship between the five discrete emotion variables happiness, anger, sadness, fear and disgust and the two affective space variables valence (left column) and arousal (right column).

Experiment 3

In order to directly test the predictions of the regression model on discrete emotions, an additional experiment was designed. Following the above analyses one would expect faster LDRTs to both happiness and fear-related words and slower responses to disgust-related words in a LDT. Since the backward elimination regression did not reveal effects of valence or arousal, we predict that discrete emotion effects are still observed even when the stimulus material is controlled for levels of valence and arousal (according to the dimensional affective space model). Five stimulus conditions were created containing words which, according to the discrete emotion model, are related to either happiness, disgust, fear, anger, or no other discrete emotion (i.e., neutral). The neutral condition consisted of words that show overall low levels of discrete emotion intensities. Sadness was not included as a further condition in the experiment because the German database that provides the discrete emotion norms does not contain sufficient sadness related stimuli to fulfill the high matching standards used in this study. Still, based on the regressions analyses presented above one would not have predicted sadness related effects on the lexical decision performance data. Across all conditions, arousal was carefully controlled, and as an additional constraint, the three negative conditions did not differ in valence. Both the dimensional and the categorical model predict a valence effect with faster responses to happiness related words, intermediate responses to neutral and slowest responses to negative words (at intermediate levels of arousal). Since all three negative discrete emotion conditions have similar levels of valence and arousal, the dimensional models would not predict LDRT differences between them. In contrast, we expected to find strong discrete emotion influences on word processing. Following the direction of the respective beta values from the regression analysis, we predict to observe slowed-down processing of disgust-related and speeded processing of happiness related words, with LDRTs to anger and fear-related words lying in between. Even between the latter two discrete emotion conditions a slight processing advantage for fear-related words could be predicted based on differences in the respective betas in Table 3.2.

Materials and Methods

Ethics

The authors took care that this study was conducted in accordance with the declaration of Helsinki and under the ethical guidelines of the German science foundation, although the study was not presented to and therefore not approved by any ethical committee or institutional board. Since the lexical decision paradigm is a standard paradigm in psycholinguistic research that involves no harm to the subjects, collects no personally critical information and has a long history in psycholinguistic research, a specific approval for this study was considered not necessary by the authors. All subjects were informed prior to their inclusion in the study on their right to decline to participate and to abort the experiment without consequences, and they were informed about the goals of the study. All participants gave their informed consent verbally prior to their inclusion. Written consent was not considered to be necessary by the authors since verbal consent already is a legal contract according to the German law. The authors alone are responsible for any decision concerning the ethics of this study.

Participants

A total of 21 native German subjects (19 female; 19 right handed, 1 reporting to be ambidextrous; mean age = 25.4, S.D. = 6.6, range = 19 to 42), recruited at the Freie Universität Berlin, participated in this study. Some of them received course credit for participation, others participated without recompense.

Materials

Stimulus material consisted of 125 nouns taken from the DENN-BAWL (Briesemeister et al., 2011a) and an equal number of nonwords. Within the word set, five conditions (happiness, neutral, fear, anger, disgust) were constructed, each containing 25 items of 4-6 letters length. Words defined as being neutral for this study had valence ratings lying between -0.5 and +0.5 according to the BAWL-R (Võ et al., 2009) and low discrete emotion intensities (mean discrete emotion ratings below 2.25). 'Positive' words had a valence rating above 1 and their happiness rating was higher than their respective rating in any other discrete emotion category. 'Negative' words, finally, had a valence rating below -1. Words in disgust condition had higher disgust than fear, sadness or anger values, equivalent relations were used to define fear and anger conditions.

All five conditions were matched on arousal [mean arousal (and SD) for happiness = 3.4 (0.5); for fear = 3.4 (0.4); for anger = 3.4 (0.6); for disgust = 3.2 (0.4); for neutral = 3.3 (0.4)] as well as their number of letters, syllables, phonemes and orthographical neighbors, their frequency, their imageability and their averaged bigram frequency using an ANOVA ($F < 1$). Additionally, the three negative basic emotion conditions were matched on valence [mean valence (and SD) for anger = -1.5 (0.4); for fear = -1.6 (0.4); for disgust = -1.6 (0.4), $F < 1$; mean valence (and SD) for happiness = 1.9 (0.5); for neutral = 0.0 (0.3)]. Estimates were taken from the BAWL-R.

Nonwords were created by selecting an additional 125 words of 4-6 letters length from the BAWL-R and replacing one or two letters, vowels with vowels and consonants with consonants, thus creating pronounceable but meaningless letter strings. They did not differ from words in length and number of syllables in a t-test ($t < 1$).

Procedure and data preparation

Participants were seated in a quiet room in front of a 15 in. laptop screen. They were instructed to decide as fast and as accurate as possible whether a presented letter string is a correct German word or a nonword. The decision was made using left and right index finger, lying on the SHIFT buttons. The button-to-response assignment was counterbalanced across subjects. After nine practice trials not part of the stimulus set and therefore excluded from any analysis, the experimenter left the room, provided that subjects did not have further questions.

Stimuli were presented by Presentation 9.9 software (Neurobehavioral Systems Inc., Canada) in randomized order in the center of the screen, written in black uppercase letters (font type “Arial”, size 24) on a blank white screen. Each trial began with a fixation cross (+) presented for 500ms in the center of the screen, replaced by the stimulus (500ms) and another fixation cross, presented until button press.

For analyses, error-free mean LDRTs were calculated for each condition and each participant. Outliers (3.7%), defined as responses faster or slower than the individual mean RT ±2 S.D., were excluded from analysis. For error analyses, behavioral errors were summed up per participant and condition. Subjects committed 7.5% errors on average. One subject was excluded having committed more than 20% behavioral errors. All analyses were computed using SPSS software at an a-priori significance level of 0.05.

Results

A repeated measures ANOVA over all five conditions (happiness, neutral, fear, anger, disgust) revealed a significant discrete emotion effect in LDRTs [$F(4,16) = 9.072$, $p < 0.001$]. Planned pairwise comparisons using matched pairs t-tests revealed faster responses to happiness related words (mean = 682.6 ms, S.D. = 128.4 ms) when compared to neutral words (mean = 702.0 ms, S.D. = 118.0 ms; $t(18) = 2.625$, $p = 0.017$). Correct recognition of disgust-related words (mean = 737.4 ms, S.D. = 129.9 ms) took significantly longer than recognizing fear (mean = 714.6 ms, S.D. = 130.4 ms; $t(18) = -2.349$, $p = 0.030$) or anger related stimuli (mean = 710.9 ms, S.D. = 127.8 ms; $t(18) = -2.272$, $p = 0.035$). All three negative conditions yielded in slower LDRTs than happiness related words (happiness vs. disgust: $t(18) = 5.280$, $p < 0.001$; vs. fear: $t(18) = 3.973$, $p = 0.001$; vs. anger: $t(18) = 3.242$, $p = 0.004$), but unlike disgust, neither fear nor anger related words differed from neutral stimuli (neutral vs. disgust: $t(18) = -3.795$, $p = 0.001$). These results are also depicted in Figure 3.2.

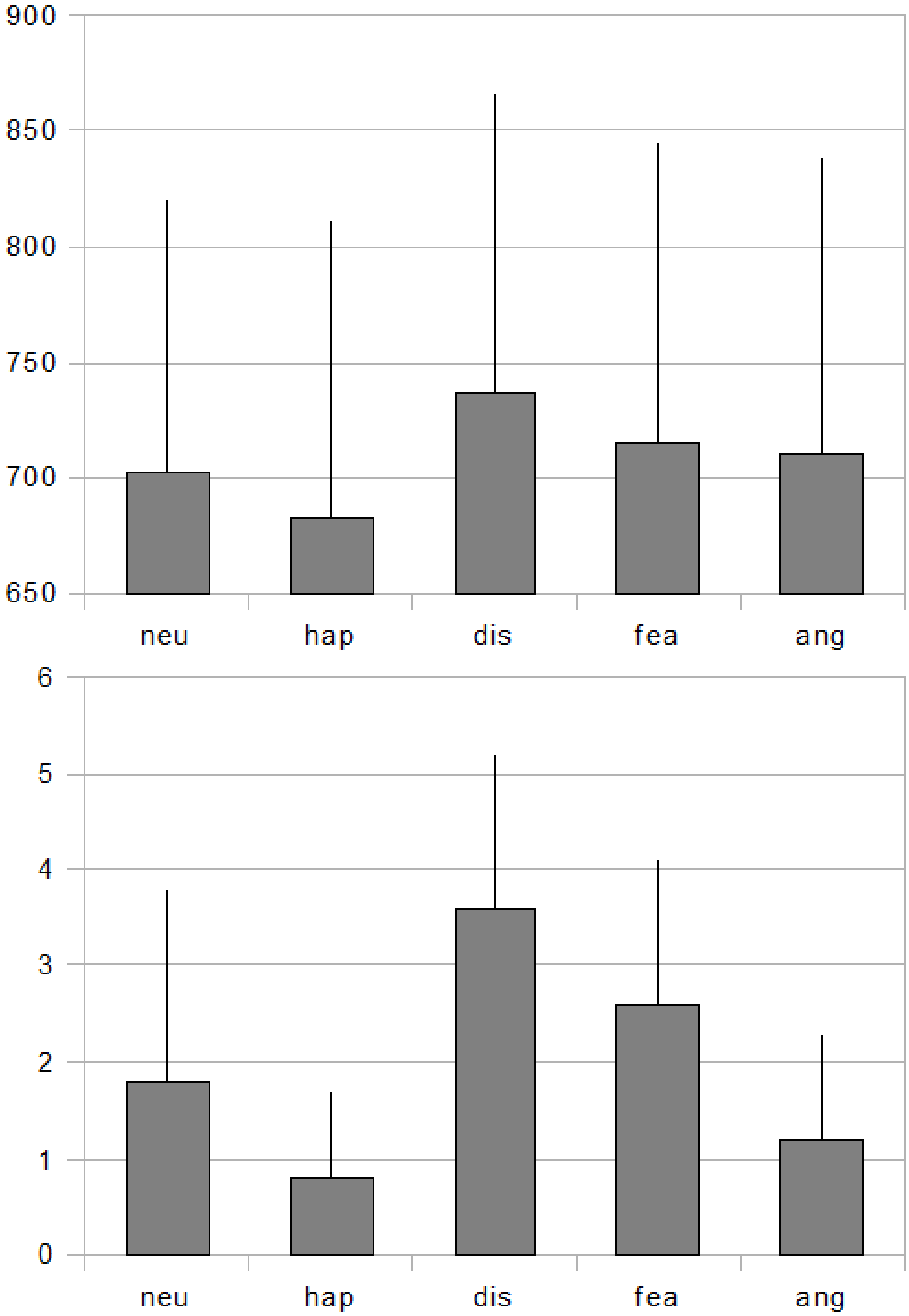

Figure 3.2: Mean response times in ms (upper part) and summed error rates (lower part) for the lexical decision task. Error bars represent one standard deviation.

Analysing the error rates (ERR), a repeated measures ANOVA over all five conditions (happiness, neutral, fear, anger, disgust) revealed a significant effect [$F(4,15) = 19.970$, p

< 0.001]. Planned pairwise comparisons using matched pairs t-tests revealed more errors while recognizing disgust-related words (mean sum of errors = 3.6, S.D. = 1.6) than in any other condition (disgust vs. neutral: $t(18) = 4.487$, $p < 0.001$; vs. fear: $t(18) = 3.012$, $p = 0.007$; vs. anger: $t(18) = 5.811$, $p < 0.001$; vs. happiness: $t(18) = 7.520$, $p < 0.001$). Fear-related stimuli (mean sum of errors = 2.6, S.D. = 1.5) lead to more errors than anger related (mean sum of errors = 1.2, S.D. = 1.1; $t(18) = 4.762$, $p < 0.001$), happiness related (mean sum of errors = 0.8, S.D. = 0.9; $t(18) = 6.514$, $p < 0.001$) and neutral stimuli (mean sum of errors = 1.8, S.D. = 2.0; $t(18) = 2.212$, $p = 0.040$). Happiness and neutral condition differed significantly ($t(18) = -2.730$, $p = 0.013$).

Discussion

Discrete emotion conditions significantly affect subjects LDRTs and error data in visual word recognition even when the stimuli are controlled for their levels of arousal and valence (the latter within the 'negative' conditions). As such, the present study supports a discrete emotion model in visual word recognition that incorporates an explanatory value which is superior to the standard two-dimensional affective space model or the categorical valence model. The LDT results resemble the predictions made following the above regression analyses. In an automatic selection procedure, the three discrete emotion categories happiness, fear and disgust were selected as the only affective variables predicting word recognition performance. Neither valence nor arousal explained additional variance. A subsequent linear multiple regression confirmed these predictors, extended by the observation that such a discrete emotion model behaves comparably well and accounts for just as much variance as a dimensional valence-arousal model (Kousta et al., 2009; Larsen et al., 2008) or a categorical model (Estes & Adelman, 2008a, 2008b).

Following the criticisms of Kousta et al. (2009) in response to Estes and Adelman (2008a), the final experimental study used German nouns rated for valence, arousal and five discrete emotions to overcome the methodological problems associated with the ANEW data. A processing advantage of happiness related words and a slowed processing of disgust-related words compared with neutral words was observed. Fear-related words could not be differentiated from neutral words in terms of their LDRTs and also did not show the predicted processing advantage compared with anger-related words. But looking at the error data, it seems that the participants showed a (not predicted) trade-off, when fear-related words led to more errors compared to the neutral and the anger conditions. Probably, this speed-accuracy trade-off could be attributed to differences in the lexical decision paradigm employed here as compared with that of the ELP (e.g., shorter inter-trial intervals, no feedback, shorter stimulus presentation duration), but this explanation needs to be further examined in subsequent studies.

Overall, these results have two immediate implications: First, given the data we were not able to replicate the observed processing advantage of both positive and negative words, as proposed by Kousta et al. (2009). In contrast, our data correspond to earlier findings, showing that processing of negative words is slowed when emotional and neutral words are controlled for their level of arousal (Estes & Adelman, 2008a, 2008b; Hofmann et al., 2009), which is best explained by a non-linear relationship between negative valence, arousal and LDRTs (see Figure 2 in Larsen et al., 2008). Only high arousal words show the proposed processing advantage, whereas negative valence itself seems to slow LDRTs. As such, our data support automatic evaluation approaches (Estes & Adelman, 2008a, 2008b; Murphy & Zajonc, 1993; Pratto & John, 1991) that propose a fast processing of stimulus' valence. The contribution of arousal to this process, however, is not clear yet, although first neurophysiological studies indicate that words' arousal may alter early lexico-semantic processing independent of affective evaluation (Herbert et al., 2008; Hofmann et al., 2009; Kissler, Herbert, Winkler & Junghofer, 2009).

Secondly and most important, valence and arousal are not sufficient to explain subjects' word recognition performance within negatively valenced words. A simple positive-negative evaluation does not explain the processing differences within negative words with slowed LDRTs and higher ERR for disgust-related words, nor does it account for the relatively slowed processing and decreased ERR for fear-related words. Thus, neither a continuous valence arousal model of affective space (Kousta et al., 2009; Larsen et al., 2008) nor a categorical valence model (Estes & Adelman, 2008a) can explain the performance effects within these negative word categories. Additional knowledge of discrete emotion category membership is required to explain the performance differences. Although the processing of negative words is slowed in general, different processes seem to distinguish disgust, fear and anger related words. Disgust words are processed slowest, thus seem to attract most processing resources according to the automatic evaluation hypothesis (Murphy & Zajonc, 1993; Pratto & John, 1991). In contrast, fear-related words show a relative processing facilitation, indicated by faster and more accurate responding as compared with disgust-related words. In general, we propose contextual learning as suggested by Barrett et al. (2007) and as described in the introduction to explain these effects. The contextual learning hypothesis refers to the assumption that discrete emotion categories acquired during early childhood may facilitate the perception of discrete emotions in different circumstances and that the perception itself is moderated by the use of language (see also Barrett et al., 2007 for a discussion of the tight link between emotion and language). The data presented here suggests that contextual learning is indeed specific for discrete emotions and less powerfull for the learning of dimensional or bi-modal models.

In sum, with the highly concordant data from different analyses performed in different languages we present strong evidence for the existence of a discrete emotion specificity in visual word recognition. These results can be taken as an indication that the dimensional models or bi-modal categorical models of affective space are underdetermined in explaining human performance in visual word recognition (Lewis et al., 2007). The results presented here complement a previous study by Stevenson et al. (2011), which examined explicit evaluative judgments of emotionally and sexually arousing words on 11 affective variables: the three affective dimensions, five discrete emotion categories and three additional rating of sexual categories. Based on a data-driven factor analysis approach, four independent factors were identified that account for most of the variance in the subjective ratings. Three out of these four factors represent the discrete emotions happiness, disgust, and a basic aversive category (covering both fear and sadness), the fourth factor representing a sexual category. Affective dimensions, in contrast, did not explain much variance in the subjective ratings. Thus, the present results together with the Stevenson et al. (2011) study demonstrate the appropriateness of discrete emotion categories in explaining affective rating behavior, and furthermore, with the lexical decision data presented above we are able to show that discrete emotion effects can also be observed in visual word recognition, where the processing of the emotional content is incidental to the task requirements. Of note here is that Stevenson et al. (2011) observed sex differences in their rating data, a question that could not be addressed with the present study because of an unbalanced proportion of female and male participants. It remains for future studies to investigate whether sex related differences can be observed within discrete emotion effects on the LDT.

Implications for future studies.

While the overall performance of dimensional models is comparable to that of a discrete emotion model, we show that a two dimensional perspective - regardless of the specific valence conception (Estes & Adelman, 2008a, 2008b; Kousta et al., 2009; Larsen et al., 2008) - fails to correctly predict discrete emotion effects for negative words in visual word recognition. Still, this paper is no more than a first glimpse on discrete emotion effects on word processing, leading to several implications for future studies. First of all, it would be interesting to see which further discrete emotion variables affect word processing. While sadness ratings are already available in English and in German (Briesemeister et al., 2011a; Stevenson et al., 2007), further discrete emotions have been suggested in the literature (i.e., surprise, Ekman, 1992; Izard, 1977; Panksepp, 1998).

Furthermore, discrete emotion effects in single word processing should not be specific to lexical decision but generalize to other word recognition tasks. If contextual learning is the basis of the discrete emotion effects discussed here, we would predict similar effects in naming and recognition memory performance for single words. Studies in the context of discrete emotion influences on attention (e.g., in the emotional Stroop task, see Thomas et al., 2007) may be of special interest, too. Shifted attention is commonly used to denominate effects of negative valence in word processing (e.g. Windmann et al., 2002), and different attention demands across the discrete emotion categories could bridge word processing and the underlying neural systems for discrete emotions.

Discrete Information Effects First, Continuous Later?

Chapter 04

This chapter has previously been published as[3]:

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Abstract

Manipulations of either discrete emotions (e.g. happiness) or affective dimensions (e.g. positivity) have a long tradition in emotion research, but interactive effects have never been studied, based on the assumption that the two underlying theories are incompatible. Recent theorizing suggests, however, that the human brain relies on two affective processing systems, one working on the basis of discrete emotion categories, and the other working along affective dimensions. Presenting participants with an orthogonal manipulation of happiness and positivity in a lexical decision task, the present study meant to test the appropriateness of this assumption in emotion word recognition. Behavioral and electroencephalographic data revealed independent effects for both variables, with happiness affecting the early visual N1 component, while positivity affected an N400-like component and the late positive complex. These results are interpreted as evidence for a sequential processing of affective information, with discrete emotions being the basis for later dimensional appraisal processes.

3 In the published paper, the order of the different sections differs from the order chosen here, where a more conventional sequence with the methods section following directly after the introduction was chosen.

Introduction

Two main conceptions have been proposed to best describe human emotions, each being in accordance with convincing empirical data. On the one hand, a class of theories assumes that emotions are processed along a limited number of affective dimensions (Russell, 2003; Wundt, 1896). The 'core affect' theory (Barrett & Bliss-Moreau, 2009; Russell, 2003; 2005; 2009), for example, assumes that emotions are “grounded in continuous and fluctuating affective states described as pleasant or unpleasant, with some level of arousal” within the core of the body (cf. Wilson-Mendenhall et al., 2013, p. 1). Within this class of theories, two affective dimensions, i.e. valence (ranging from a pleasant to an unpleasant pole) and arousal underlie human emotional experiences and evaluations, which is well in line with many empirical findings (Barrett & Bliss-Moreau, 2009; Russell, 2003). Discrete emotion theories, on the other hand, assume a limited set of functionally distinct emotion categories (Darwin, 1872; Ekman, 1992; Panksepp, 1998), which is primarily supported by studies that compared affective responses across different cultures (Elfenbein, 2013) and species (Panksepp, 1998). The existence of discrete emotions like fear, anger, disgust, sadness, and happiness is widely accepted, even though less consensus is reached regarding further emotions (like pride) or a common definition.

Even though discrete emotion models and dimensional models of affective space have traditionally been proposed as opposing viewpoints, several more recent models seek to integrate both conceptions in a single theoretical framework (Panksepp, 2008; Russell, 2005). The core affect theory mentioned above, for example, explicitly distinguishes between the two-dimensional core affect, which is seen as the first order state underlying continuous fluctuations in emotional life, and second order emotional meta-experiences that are derived from it (Russell, 2005). Discrete emotions, in this view, “are complex Gestalts that typically include simpler, more primitive feelings of Core Affect” (cf. Russell, 2005, p. 27), i.e. they depend on and are derived from the core affect. An alternative unifying framework is provided by Panksepp (2008), whose model is based on neurophysiological and neuroanatomical evidence for discrete emotional states in the mammalian brain (Panksepp, 1998). Panksepp assumes that discrete emotions are genetically ingrained basal processes that originate in subcortical circuits, such as the periaqueductal gray (PAG), while affective dimensions depend on neocortical circuits such as the dorsolateral prefrontal cortex. In the neocortex, discrete emotions are adapted to and shaped by sociocultural demands, with one important function being to “cluster [the formally discrete emotions] into constellations of positive and negative affect” (cf. Panksepp, 2006b, p. 22). Following this view, affective dimensions are clearly derived from more basal discrete emotions, which is the exact opposite sequence when compared to the core affect model. Moreover, Panksepp explicitly emphasizes that three (temporally succeeding) levels-of-analysis must be distinguished: (a) a primary process-level where discrete emotions arise from subcortical processes, (b) a secondary process-level where emotions from the first process-level are transformed into conditioned responses based on classical and instrumental conditioning (e.g. fear-conditioning in LeDoux, 2000) and (c) a tertiary process-level that represents interactions of the previous levels with higher-order, neocortical cognitive processing (Panksepp & Watt, 2011).

The most obvious discrepancies between these two unifying frameworks relate to the different time frames of emotion processing, which is why temporally more fine-grained analyses have been asked for (Barrett & Wager, 2006). According to Russell (2005; 2009), discrete emotions are derived from fluctuating states best described in terms of affective dimensions, which implies a succession with temporal priority for the dimensional core affect. The hierarchical model suggested by Panksepp (2008), in contrast, predicts a temporal order of processing where discrete emotions based at first and second level precede a third one related to affective dimensions. To test these opposing predictions, we employed an ERP study of emotion effects in word recognition using a LDT.

Previous research on visual word processing using the ERP methodology documents that EEG recordings provide an excellent measure to investigate the temporal dynamics of implicit affective processing as triggered by the LDT (for a review, see Citron, 2012). Different temporally early and late ERP components have been identified to reveal effects related to emotional processing. The N1 component, peaking around 100ms, is sensitive to differences in early attentional resource allocation for positive versus negative stimulus categories (words: Hofmann et al., 2009; pictures: Foti, Hajcak & Dien, 2009). Such early effects are visible before the stimulus is analyzed in full detail, and, in case of emotional words, have been shown to result from conditional learning (Fritsch & Kuchinke, 2013) as it would be expected by secondary level processes (Panksepp & Watt, 2011). Similarly, a negative deflection peaking between 200-300ms is visible in word recognition tasks around the time frame of word identification (early posterior negativity, EPN; Citron, 2012), modulated by implicit and automatic processing of affective information irrespective of its polarity (e.g., Kissler et al., 2009; pictures: Foti et al., 2009). Later components that reflect emotional processing like the N400 and the LPC (late positive complex, around 500-800ms) are discussed to indicate higher-order evaluative processes (words: Kanske & Kotz, 2007; pictures: Foti et al., 2009), in accordance with the description of Panksepp's tertiary process-level.

While there is a history of dimensional emotion effects in word recognition (Citron, 2012), recent work suggests that word processing is also affected by discrete emotion information when the material is controlled for dimensional emotion effects (Briesemeister et al., 2011a, 2011b; see also Ponz et al., 2013a; Silva et al., 2012). With an orthogonal manipulation, it should thus be possible to examine temporal differences of dimensional and discrete emotion processing and their role in differentiating words from nonwords. Based on Panksepp's model of hierarchical emotion processing (Panksepp, 2006a) we predicted that (conditioned) discrete emotion information affects early ERP components (N1, EPN), whereas dimensional emotion information affects later ERP components (N400, LPC) as these address post-lexical cognitive evaluations at the tertiary process-level in neocortex (Panksepp & Watt, 2011). The reverse result-pattern would be supported by the core affect theory (Wilson-Mendenhall et al., 2013).

Experimental Procedure

Stimulus material

The stimulus material consisted of 120 German 4-to-8-letter nouns and an equal number of nonwords. A 2(happiness)*2(positivity) within-subject design was employed, with 30 items per condition. Happiness norms were derived from the DENN-BAWL database (Briesemeister et al., 2011b) and valence norms from the BAWL-R (Võ et al., 2009). Words with happiness ratings below 2.6 on a 5-point Likert scale were classified as weakly related to happiness (lowHap), words with happiness greater than 2.6 as highHap. Words with valence ratings between -0.7 and 0.7 were classified as neutral (neu), and words with valence ratings between 1 and 3 as positive (pos). This resulted in four orthogonal conditions with uncorrelated happiness and valence scores throughout the entire stimulus set (r=0.09). LowHap+neu (e.g. “HUHN”, engl. “CHICKEN”; happiness=2.3, positivity=0.5), lowHap+pos (e.g. “PRIVILEG”, engl. “PRIVILEGE”; happiness=2.4, positivity=1.3), highHap+neu (e.g. “SATIRE”, engl. “SATIRE”; happiness=2.9, positivity=0.5) and highHap+pos conditions (e.g. “EKSTASE”, engl. “ECSTASY”; happiness=2.9, positivity=1.4) were controlled for their average level of arousal, imageability, (log-)frequency per million, bigram frequency, orthographic neighborhood size, frequency of orthographic neighbors, frequency of higher frequent orthographic neighbors, as well as their mean number of letters, syllables, phonemes and higher frequency orthographic neighbors using ANOVAs (all F's < 1). Where possible, highhap words were chosen to actually elicit a good feeling, while positive words described generally desirable things. To ensure the orthogonality of the manipulation, the means of all the control variables were also matched for the highHap versus lowHap, and for the neu versus pos contrasts as verified by means of pairwise t-tests (all t's < 1). These stimulus characteristics are summarized in Table 1. Pronounceable but meaningless nonwords were constructed by changing one letter from 120 words that were not part of the stimulus set, matched to the words on number of letters and syllables (t's < 1).

Pilot study participants

Before the EEG study, a behavioral pilot study was run. Twenty-three participants (18 female) were recruited at the Ruhr-University Bochum. All reported having a dominant right hand, normal or corrected-to-normal vision, German as their first language, no current medication affecting the central nervous system and no reading disorders. Their mean age was 26 years (SD=5, range 19 to 38). One participant aborted the experiment and was thus excluded from all analyses.

EEG study participants

For the EEG study, nineteen participants (13 female) were recruited at the Free University Berlin. All reported having a dominant right hand, normal or corrected-to-normal vision, German as their first language, no current medication affecting the central nervous system and no reading disorders. Their mean age was 26 years (SD=5, range 20 to 42). One participant was excluded from all analyses because of overall noisy data (ERR >15%, noisy ERPs).

Ethics

The study was approved by the local ethics committee. All experiments were conducted in accordance with the principles expressed in the Declaration of Helsinki. Informed consent was obtained from all participants.

Procedure

The pilot and the EEG study used the exact same stimulus material and followed the same procedures, except for the EEG preparation described below. The experiment started with nine training trials that were not part of the stimulus set to familiarize the participants with the task. Each trial began with the foveal presentation of a fixation cross (+) for 500ms, followed by the stimulus (500ms) at the same position. If the response (left CTRL = nonword, right CTRL = word) was not given within the stimulus duration, the stimulus was replaced by a fixation cross (1000ms), resulting in a maximum trial duration of 2000ms. Between trials, a fixation cross (jittered 0-500ms) served as inter-stimulus interval. All stimuli were presented in randomized order in black uppercase Arial 24 font (~0.56° vertical visual angle) on a light gray background, controlled by Presentation 14.9 software (Neurobehavioral Systems Inc., Canada). Participants were instructed to respond as fast and as correct as possible.

For the EEG study, data was collected in a session comprised of three different experiments. The LDT was always the last experiment of the session, with none of the previous experiments being related to lexical or emotional processing. Continuous EEG data were recorded by 27 active electrodes (actiCap system, Brain Products, Germany) attached to a 32-channel amplifier (Brainamp, Brain Products, Germany, sampling rate 500 Hz). They were placed according to the international 10–20 system at the positions FP1, FP2, F3, F4, F7, F8, FC1, FC2, FC5, FC6, Fz, CP1, CP2, CP5, CP6, P3, P4, P7, P8, Pz, C3, C4, Cz, T7, T8, O1 and O2 and referenced to the right mastoid (with an additional electrode being placed on the left mastoid for later re-referencing). Four electrodes were placed above and below the right eye and on the outer canthus of each eye to record the eye movements. The impedances were kept below 18 kΩ for all electrodes.

Data preparation

Mean LDRTs were calculated for each condition and each participant after exclusion of nonresponders, behavioral errors and outliers, defined as responses outside 2 SD of the individual mean LDRT. ERRs were calculated as summed errors per condition and participant.

EEG raw data were filtered (0.1-30 Hz, 50 Hz notch filter) and corrected for artifacts, drifts and amplifier blocking via visual inspection using BrainVision Analyzer software (BrainProducts, Germany). Blinks and eye movements were removed using independent component analysis, and remaining artifacts defined as amplitudes greater than 60µV or smaller than -60µV were excluded using an automatic detection procedure after re-referencing to averaged mastoids. The remaining data (~93 of 120 trials per subject) were segmented relative to the stimulus onset (200 to 800ms), with all stimuli excluded from behavioral analysis being excluded from EEG analysis as well. Finally, baseline corrected (-200 to 0ms) averages were calculated per participant and per condition.

Based on visual inspection of the ERPs and in accordance with the literature, four components were exported for further analysis of emotion related effects. Based on Hofmann et al. (2009), who report an emotion related modulation of the N1 at 100ms (see also Fritsch & Kuchinke, 2013), an automatic peak detection procedure was used to identify the individual global negative deflection peak in the time window between 70 and 130ms. The time window surrounding the individual peaks ±20ms was exported and averaged for analysis. Topographies suggested a bilateral fronto-central effect, thus the electrodes Fp1, F7, F3, FC5 and FC1, as well as Fp2, F8, F4, FC6 and FC2 were clustered together. For the analysis of the EPN, the data was re-referenced to the average of all electrodes. Then, the individual global negative deflection peak in the time window between 200 and 330ms was identified. Given that the EPN is characterized as a broad negative deflection, the individual peaks ±40ms were exported and averaged for two occipito-temporal clusters including the electrodes O1, P3, P7, and T7, as well as O2, P4, P8, and T8 (Kissler et al., 2009).

Visual inspection of the grand averages revealed a small N400-like negative deflection (380-440ms) and averaged amplitudes over this time window were exported for analysis. Following Kanske and Kotz (2007), electrodes were summarized in four clusters: anterior-left (Fp1, F7, F3, FC5, FC1), anterior-right (Fp2, F8, F4, FC6, FC2), posterior-left (CP5, CP1, P7, P3, O1) and posterior-right (CP6, CP2, P8, P4, O2). A similar approach was chosen for the analysis of the LPC in the 600-800ms interval. Based its centro-parietal distribution (Citron, 2012), a cluster comprising the electrodes P3, P4, Pz, CP1, CP2, Cz, C3, and C4 was used for LPC analyses.

In addition to the emotion related differences, a word versus nonword contrast was calculated to allow for a better interpretation of the results and their relation to semantic processing. Visual inspection of the ERPs revealed greater, slightly right-lateralized negativity for nonwords between 380 and 700ms peaking around 400ms, which is well in line with the N400 literature (Braun et al., 2006; Briesemeister et al., 2009; Holcomb et al., 2002). Based on Braun et al. (2006) and Holcomb et al. (2002), who both report a stimulus type main effect for the words versus nonwords contrast on the entire scalp, the same four electrode clusters as for the N400-like analysis described above were used.

Finally, a correlation analysis was conducted for each ERP component that revealed a significant emotion effect. For each participant and each electrode cluster the happiness contrast (highHap–lowHap) and the positivity contrast (pos–neu) was correlated with the net LDRT emotion effects, calculated as LDRT(highHap)–LDRT(lowHap), and LDRT(pos)–LDRT(neu), respectively (see Silva et al., 2012 for a detailed description). All analyses were computed using SPSS 13.0 (SPSS Inc., USA) at an a-priori significance level of 0.05.

Results

Pilot study

A repeated measures ANOVA for LDRTs yielded significant main effects of happiness ($F(1,21)=11.995$, $p=0.002$, $\eta 2=0.364$) and positivity ($F(1,21)=5.206$, $p=0.033$, $\eta 2=0.199$), but no significant interaction ($F(1,21)=2.270$, $p=0.147$, $\eta 2=0.098$). Words highly rated on happiness (highHap) were processed faster (M=623ms, SD=97ms) than words weakly related to happiness (lowHap; M=643ms, SD=109ms). Neutral words (neu; M=627ms, SD=101ms) were processed faster than positive words (pos; M=640ms, SD=105ms). Planned pairwise comparisons revealed three significant effects, that is slower responses for lowHap+pos words (M=654ms, SD=111ms) when compared with lowHap+neu (M=633ms, SD=108ms; $t(21)=-3.266$, $p=0.004$), with highHap+pos (M=625ms, SD=100ms; $t(21)=-4.373$, $p<0.001$), and with highHap+neu words (M=622ms, SD=98; $t(21)=-3.562$, $p=0.002$).

In the ERR analysis a significant main effect of positivity with fewer errors for neutral words (neu: M=3.0, SD=1.8; pos: M=4.1, SD=2.6; $F(1,21)=5.570$, $p=0.028$, $\eta 2=0.210$) and a significant happiness*positivity interaction ($F(1,21)=11.307$, $p=0.003$, $\eta 2=0.350$) were observed. The main effect of happiness did not reach significance ($F(1,21)=1.184$, $p=0.289$, $\eta 2=0.053$). Paired comparisons revealed smaller ER for lowHap+neu (M=2.6, SD=1.8) than for highHap+neu (M=3.4, SD=2.0; $t(21)=2.667$, $p=0.014$), as well as greater ER for lowHap+pos (M=4.7, SD=3.1) than for highHap+neu ($t(21)=-2.450$, $p=0.023$), for highHap+pos (M=3.4, SD=2.6; $t(21)=-2.668$, $p=0.014$) and for lowHap+neu words ($t(21)=-3.856$, $p=0.001$).

In summary, participants responded faster to neutral than to positive and faster to highHap than to lowHap words. This was accompanied by fewer errors to neutral than to positive words, as well as fewer errors for lowHap than for highHap within the neutral words and more errors for lowHap than for highHap within the positive words.

Behavioral results EEG study

The repeated measures ANOVA for LDRTs yielded a significant main effect of positivity (neu: M=617ms, SD=74ms; pos: M=625ms, SD=77ms; $F(1,17)=4.629$, $p=0.046$, $\eta2=0.214$), but no main effect of happiness ($F(1,17)=0.890$, $p=0.359$, $\eta2=0.050$). The happiness*positivity interaction reached significance ($F(1,17)=5.287$, $p=0.034$, $\eta2=0.237$). Pairwise comparisons revealed greater LDRTs for lowHap+pos (M=636ms, SD=91ms) than for lowHap+neu (M=612ms, SD=75ms; $t(17)=2.919$, $p=0.010$), as well as a trend indicating greater LDRTs for lowHap+pos than for highHap+pos (M=614ms, SD=70ms; $t(17)=1.847$, $p=0.082$) and for highHap+neu (M=621ms, SD=76; $t(17)=1.652$, $p=0.117$).

The ERR analysis revealed a significant main effect of positivity (neu: M=1.9, SD=1.4; pos: M=3.0, SD=2.1; $F(1,17)=4.674$, $p=0.045$, $\eta2=0.216$), but no main effect of happiness ($F(1,17)=0.418$, $p=0.526$, $\eta2=0.024$) and no interaction ($F(1,17)=0.797$, $p=0.384$, $\eta2=0.045$). In summary, participants responded faster and more accurately to neutral than to positive words. Moreover, a trend for faster processing of highHap words when compared to positive lowHap words was observed.

ERPs

The ERPs are depicted in Figures 4.1 and 4.2. A repeated measures ANOVA for the N1 comprising the within subject factors happiness (highHap/lowHap), positivity (neu/pos) and laterality (left/right) revealed a significant main effect of happiness ($F(1,17)=6.612$, $p=0.020$, $\eta2=0.280$), indicating an enhanced bilateral N1 amplitude for highHap (M=-1.3 microV, SD=1.1) versus lowHap words (M=-0.8microV, SD=1.3microV), but no main effect ($F(1,17)=0.091$, $p=0.767$, $\eta2=0.005$) or interactions related to positivity (hap*pos: $F(1,17)=0.117$, $p=0.736$, $\eta2=0.007$).

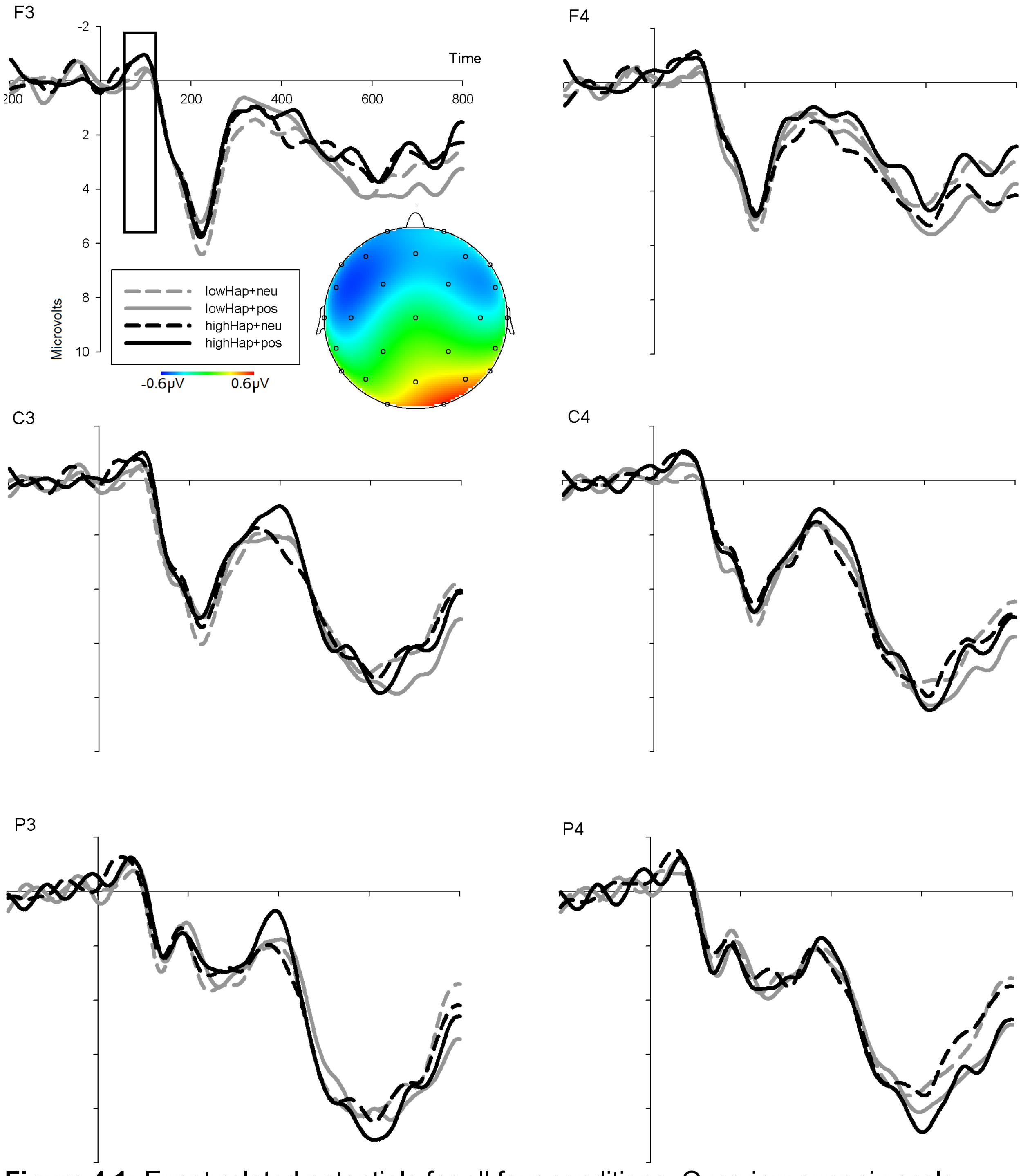

Figure 4.1: Event-related potentials for all four conditions. Overview over six scalp electrodes, including the topographies for the early happiness effect

The repeated measures ANOVA for the EPN revealed no significant main effects for positivity ($F(1,17)=0.008$, $p=0.931$, $\eta2<0.001$) or happiness ($F(1,17)=0.492$, $p=0.493$, $\eta2=0.028$) and no significant interactions (hap*pos: $F(1,17)<0.001$, $p=0.995$, $\eta2<0.001$).

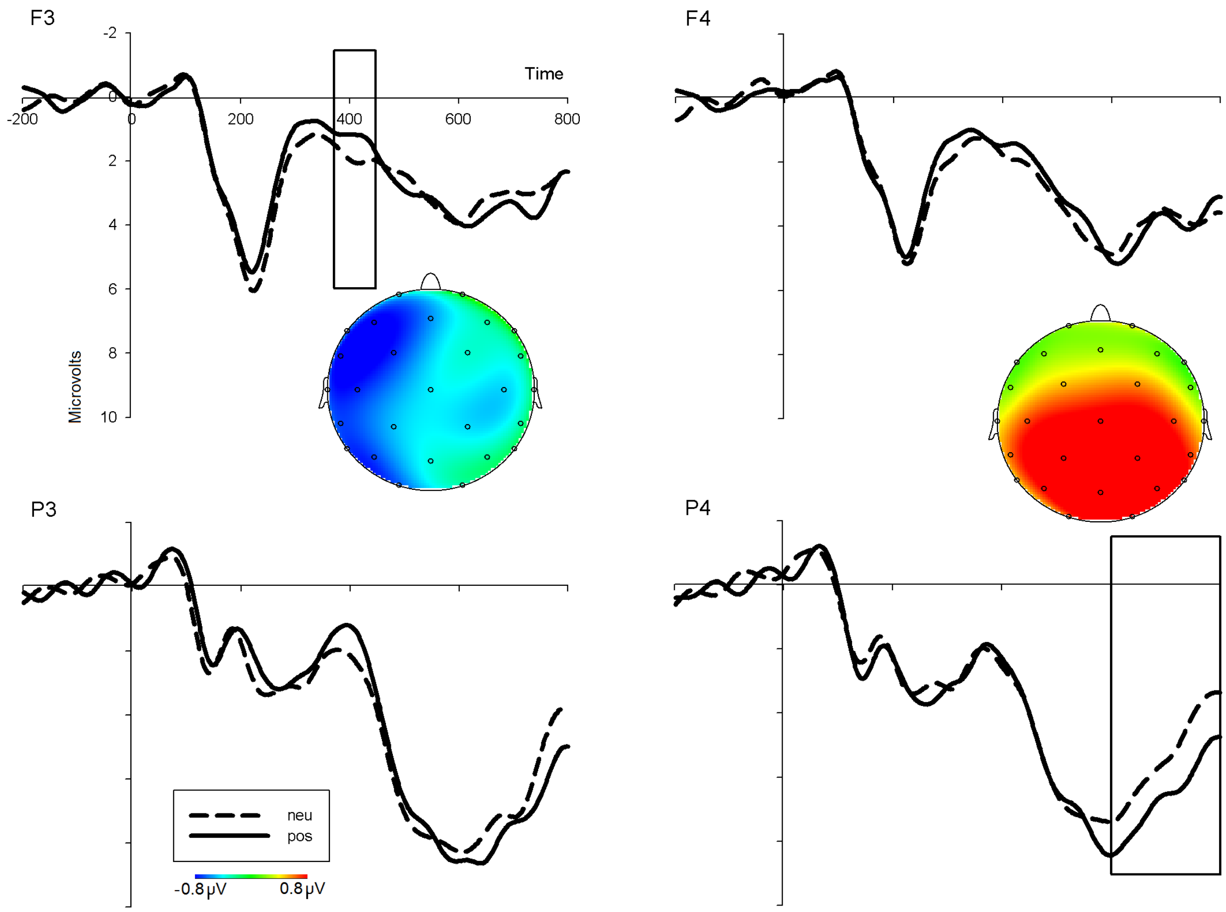

Figure 4.2: N400-like and LPC effects for positivity. Event-related potentials from four scalp electrodes, inslucing the topographies for the N400-like and LPC effects

A repeated measures ANOVA of the N400-like negative deflection including the within subject factors happiness, positivity, laterality and anteriocity (anterior/posterior) revealed no main effects of positivity (F(1,17)=2.763, p=0.115, η2=0.140) or happiness (F(1,17)=0.033, p=0.858, η2=0.002). Happiness and positivity did not interact (F(1,17)=0.960, p=0.341, η2=0.053), but the positivity*laterality interaction reached significance (F(1,17)=5.314, p=0.034, η2=0.238, see Figure 4.2). Follow-up analyses for each cluster separately revealed trends towards positivity effects in the left anterior (neu: M=1.8microV, SD=3.6microV; pos: 1.1microV; SD=3.8microV; F(1,17)=3.853, p=0.066) and posterior cluster (neu: M=1.9microV, SD=3.8microV; pos: 1.3microV; SD=3.6microV; F(1,17)=4.214, p=0.056), indicating greater negativity for positive words in left hemispheric clusters. Also for the LPC, a significant main effect of positivity (F(1,17)=7.319, p=0.015,

$\eta 2=0.301$) but no main effect of happiness ($F(1,17)=0.087$, $p=0.771$, $\eta 2=0.005$) and no interaction ($F(1,17)=0.325$, $p=0.576$, $\eta 2=0.019$) were observed, indicating a more positive-going LPC for positive (7.1microV; SD=3.0microV) than for neutral words (M=6.1microV, SD=3.0microV). In summary, a greater bilateral anterior N1 component for highHap in comparison to lowHap words, as well as a greater left hemispheric N400-like deflection and a greater LPC for positive in comparison to neutral words were observed, but not interactions between happiness and positivity.

To analyze the effect of stimulus type, a repeated measures ANOVA over the N400 time window (380-700ms) comprising the within subject factors word type, laterality and anteriocity was calculated. It revealed a main effect of word type ($F(1,17)=6.303$, $p=0.022$, $\eta 2=0.270$) driven by generally greater N400 amplitudes for nonwords (M=2.9microV, SD=2.7) than for words (M=3.8microV, SD=2.6; see Figure 4.3). The interactions of stimulus type with anteriocity ($F(1,17)=5.374$, $p=0.033$, $\eta 2=0.240$) and laterality ($F(1,17)=7.538$, $p=0.014$, $\eta 2=0.307$) as well as the triple interaction ($F(1,17)=37.673$, $p<0.001$, $\eta 2=0.689$) were also found to be significant. Follow-up analyses for each cluster separately revealed significant differences in right hemispheric anterior (words: M=3.0microV, SD=3.2microV; nonwords: 1.8microV; SD=3.3microV; $t(1,17)=3.335$, $p=0.004$) and posterior clusters (words: M=4.5microV, SD=2.4microV; nonwords: 3.4microV; SD=2.4microV; $t(1,17)=2.862$, $p=0.011$) as well as posterior left electrode clusters (words: M=5.2microV, SD=2.8microV; nonwords: 4.0microV; SD=2.8microV; $t(1,17)=2.946$, $p=0.009$).

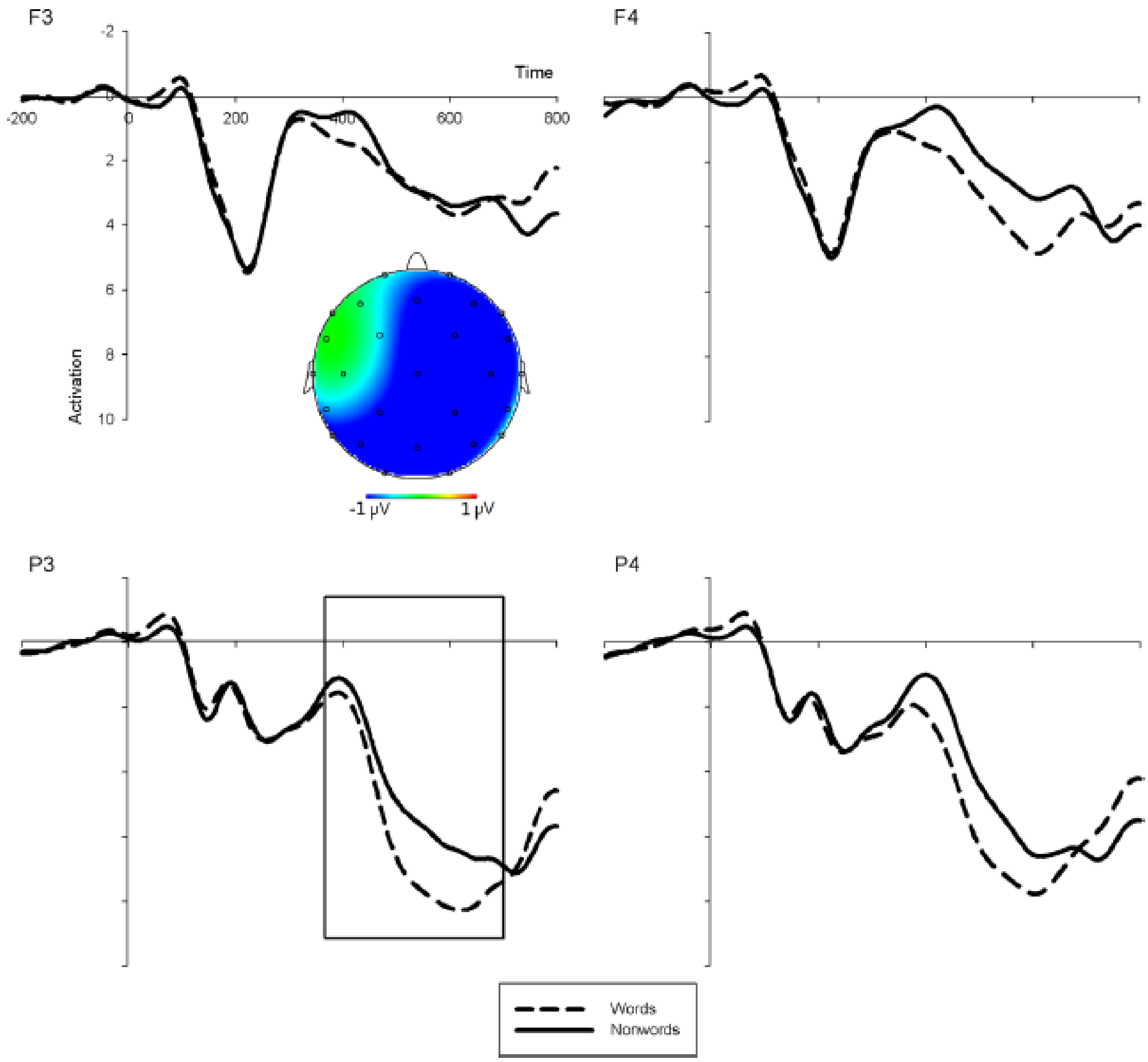

Figure 4.3: N400 effect for the word versus nonword contrast. Event-related potentials from four scalp electrodes, including the topographies for the stimulus type N400 effect

Correlation analyses

Correlating the net LDRT effects with the emotion effects for the N1 (correlations ranging from $r(16)=-0.221$ to $r(16)=0.249$, p-values between 0.304 and 0.765) and the LPC component (for happiness: $r(16)=-0.206$, $p=0.411$; for positivity: $r(16)=-0.253$, $p=0.312$) revealed no significant correlations. In case of the N400-like negative deflection, the right anterior electrode cluster comprising Fp2, F8, F4, FC6, and FC2 was negatively correlated with the individual net LDRT effect for positivity ($r(16)=-0.544$, $p=0.020$). Since the N400-like component is a negative ERP deflection, the negative correlation indicates a stronger N400-like negativity with increasing LDRT differences between positive and neutral words.

No other significant correlations between any N400-like cluster and positivity (correlations ranging from r(16)=-0.081 to r(16)=-0.386, p-values between 0.113 and 0.750) or happiness (correlations ranging from r(16)=-0.021 to r(16)=-0.395, p-values between 0.105 and 0.935) were observed.

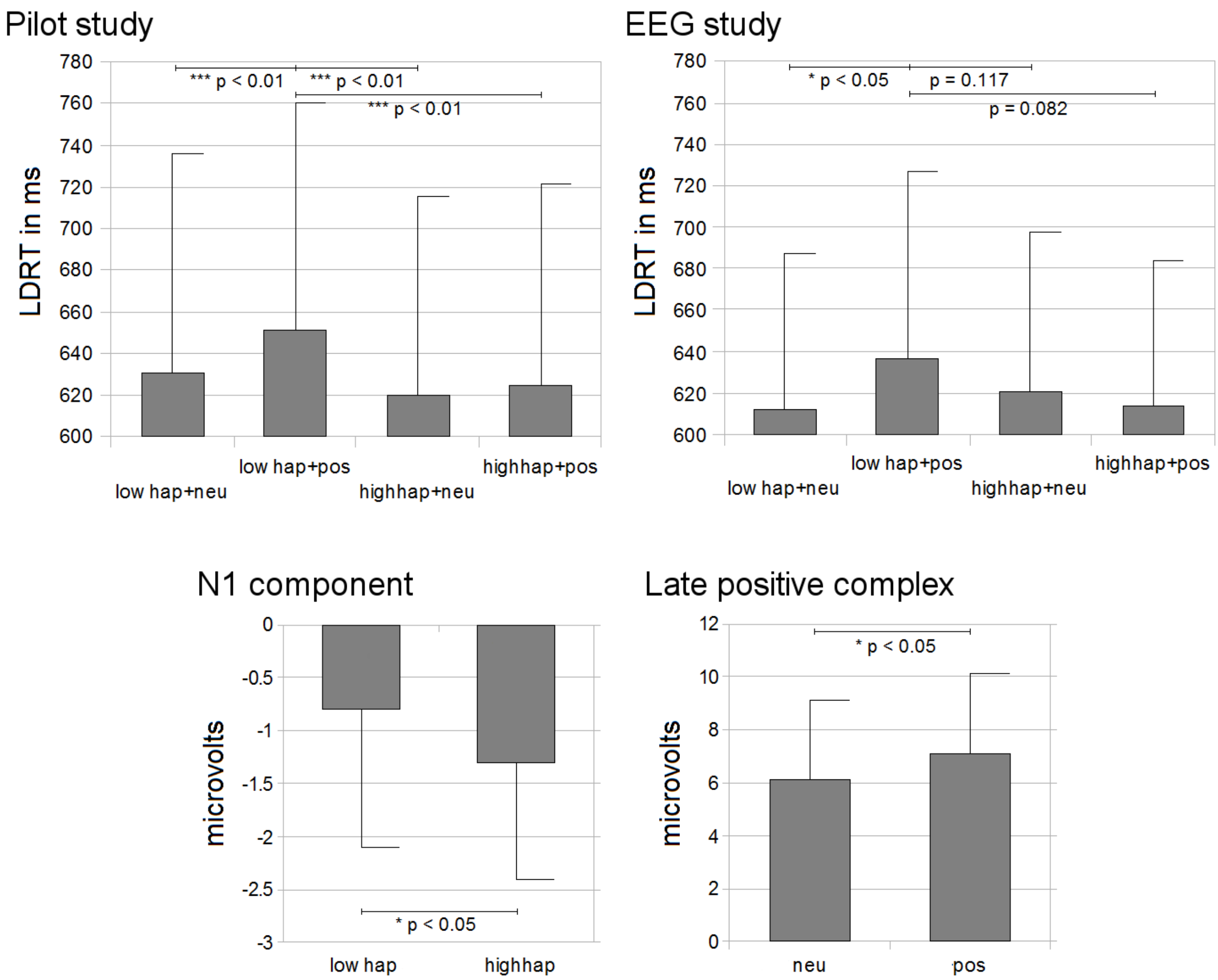

Figure 4.4: Overview of the most important effects. Upper left: Lexical decision response times (LDRT) for the pilot study. Upper right: LDRT for the EEG study. Lower left: Main effect of happiness on the N1 ERP component. Lower right: Main effect of positivity on the late positive complex.

Discussion

The present study examined predictions of Panksepp's hierarchy of emotion processing levels in word recognition. Based on the view that affective dimensions are the result of neocortical processing circuits which rely on preceding emotional processing, the hypothesis was derived that discrete emotion effects are visible earlier in the processing stream compared to dimensional emotion effects. The ERP data clearly support this notion by revealing discrete emotion effects occurring earlier than the dimensional effects when orthogonally manipulated, and in particular in a time window (70-130ms) that has previously been shown to be affected by conditioned emotional effects in visual word recognition (Fritsch & Kuchinke, 2013).

In detail, main effects of dimensional positivity were found in the behavioral analyses of both experiments, indicated by slower processing of positive than neutral words across both discrete emotion happiness conditions. An additional main effect of happiness was observed in the pilot study, driven by significantly faster processing of highHap words, which was replicated as a tendency in the pairwise comparisons in the ERP study. These effects together cannot be explained by either a discrete or a dimensional emotion model alone based on the orthogonal manipulation of both factors, showing the necessity of combined approaches in emotional evaluation (Panksepp, 2008; Russell, 2005). The facilitative happiness effects replicate previous discrete emotion findings (Briesemeister et al., 2011a, 2011b), while for the dimensional contrast facilitative and not inhibitory processing of positive words would have been expected based on the literature (Hofmann et al., 2009; Kanske & Kotz, 2007). So far, inhibitory LDRT effects are best documented for negative words (Briesemeister, Kuchinke, Jacobs, 2011b; Hofmann et al., 2009), which is explained by a need of more elaborated processing for potentially threatening and thus subjectively significant information. The explanation for the slow-down of positive compared to neutral word processing might follow comparable lines: When the material is controlled for discrete emotion measures that facilitate lexical decisions, the information conveyed by positive words at low levels of discrete emotion information require additional tertiary-level semantic (N400, LPC) evaluation and integration processes. Following Panksepp (2008), the processing of affective dimension information follows that of discrete emotion information (see discussion below) and thus relies on the availability of discrete

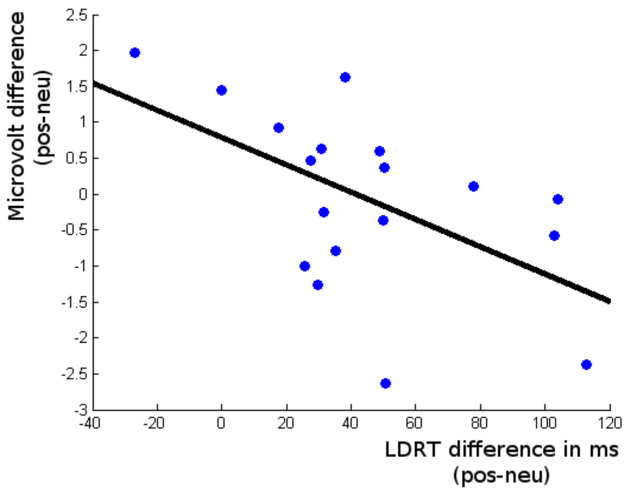

Figure 4.5: Correlation between the net positivity effect and the N400-like effect.

emotion signals (see the correlation of the two variables in Briesemeister et al., 2011b). A positive connotation like that of lowHap+pos words that gains no support from available discrete emotion signals therefore would demand additional evaluation, leading to the slower response times in both, the pilot and the ERP study. Of note is that based on the present data it seems likely that previous facilitatory effects in dimensional examinations of positive words are biased by the (sub-)category of facilitative happiness-related information.

More importantly, the ERP analyses clearly support the predicted sequential effects, with a main effect of the discrete emotion happiness on the early N1 preceding the effects of dimensional positivity on later post-lexical ERP components (N400, LPC). Early emotional ERP effects around 100ms in word recognition are discussed to index initial attentional resource allocation to quickly process potentially meaningful information (Citron, 2012). The word has not been fully identified at this processing stage, as also indexed by the later N400 effect in a word versus nonword contrast, leading to the suggestion that the activation spreads along conditioned emotionally charged lexico-semantic associations (Fritsch & Kuchinke, 2013). As the early N1 effect is only visible for the discrete emotion category, this speaks for a conditioned response based on discrete emotion information as predicted by Panksepp's secondary process-level. A similar effect is not visible for words high or low in positivity, a result that is difficult to explain in terms of the core affect theory. The core affect theory assumes that discrete emotion information is categorized by controlled processing from bodily valence-arousal states to constitute human experiences (Wilson-Mendenhall et al., 2013), and hence should not precede dimensional effects. Moreover, valence and arousal are controlled for in the happiness contrast (see Table 4.1), and an explicit processing account is unlikely at this very early processing stage.

Table 4.1: Stimulus characteristics

	lowHap +neu	lowHap +pos	highHap +neu	highHap +pos	F-value	p-value
Log frequency	2.3 (2.1)	1.8 (1.9)	1.8 (1.4)	2.2 (1.7)	0.747	0.526
Letters	6.1 (1.4)	6.2 (1.2)	6.1 (1.4)	5.9 (1.2)	0.358	0.783
Syllables	2.0 (0.7)	2.1 (0.5)	2.1 (0.8)	2.0 (0.6)	0.287	0.834
Phonemes	5.4 (1.3)	5.7 (1.3)	5.4 (1.4)	5.3 (1.2)	0.721	0.541
Arousal	2.4 (0.3)	2.5 (0.6)	2.6 (0.6)	2.5 (0.8)	0.572	0.634
Imageability	4.7 (1.3)	4.6 (1.5)	4.9 (1.4)	4.9 (1.5)	0.256	0.857
Bigram frequency	182953 (129198)	224222 (166890)	196547 (158145)	164361 (133714)	0.871	0.458
Ortho. neighbors (N)	1.7 (1.9)	2.2 (3.4)	2.2 (3.6)	1.2 (2.2)	0.915	0.436
Frequency of N	116.8 (317.7)	210.6 (568.6)	161.2 (463.2)	127.9 (524.7)	0.233	0.873
Higher frequent N (HN)	0.5 (1.4)	0.6 (1.2)	0.9 (1.6)	0.4 (1.3)	0.537	0.658
Frequency of HN	82.4 (295.0)	192.6 (533.7)	157.7 (456.2)	115.4 (505.7)	0.333	0.801

In contrast, later controlled processing at a time assumed to follow lexical access shows a predicted effect of the dimensional emotion variable. Both, the N400 component, which is known to require at least a minimum of lexico-semantic processing and is shown to differentiate words from nonwords in the present study, and, to a greater extent, the LPC as being indicative of higher-order neocortical evaluative processes (Citron, 2012) reveal this influence. The temporal sequence of these effects is consistent with the assumption that dimensional emotion information is derived from available discrete emotion information from lower-level subcortical processing through interactions with higher-order neocortical semantic processing (Panksepp & Watt, 2011). It should be noted that in emotion word recognition often smaller N400 amplitudes are reported for emotional compared to neutral words (Citron, 2012; Kanske & Kotz, 2007), whereas greater N400 amplitudes to emotionally arousing words embedded in sentences have been documented (Holt, Lynn & Kuperberg, 2009). With the greater N400 amplitudes to positive words derived from the dimensional approach, these results mirror that of the behavioral data and lead to the observed correlation between the positivity related N400 and LDRT effects over right-anterior electrodes. Thus, although no positivity related N400 effect was observed in the right anterior cluster, a strong relationship with the behavioral data is visible. This discrepancy seems related to a reversal of the N400 positivity effect (see Figure 4.5). In accordance with the significant correlation, some studies indicate that bilateral frontal electrodes explain response time variability in cognitively demanding tasks. For example, Gerson, Parra and Sajda (2005) report that response times variability is closely related to activity differences measured over bilateral frontal electrodes. Of note is that in the present study a similar negative N400-LDRT correlation is visible over the anterior-left cluster, though not significant ($r(16)=-0.386$, $p=0.113$).

Nonetheless, the majority of the results indicate an extended initial semantic analysis at post-lexical processing stages (Holt et al., 2009) for positive versus neutral words, which is further supported by the N400 effect for nonwords, which starts at the exact same point in time. Behavioral and electrophysiological indicators agree in the fact that the processing of positive words and its integration in the lexico-semantic task context is slowed-down, once the stimulus material is controlled for happiness. The LPC findings complement the N400 results. Enhanced LPC amplitudes to positive words are often reported in emotional word recognition (e.g. Citron, 2012) and commonly agreed to reveal post-lexical controlled evaluations as would be predicted, both by a psychological construction approach and by Panksepps tertiary process-levels.

As it was not possible to manipulate positive and negative dimensional and discrete emotional words within one stimulus set, we decided to focus on positive valence and happiness in the present study. Thus, it remains to be tested whether the reported results also extend to the processing of negatively valenced stimulus material. Both, the core affect theory and the Panksepp (2008) model assume that sequential processing does not differ between positive and negative emotions, and the data presented by LeDoux (2000) suggest sequential processes for fear conditioning as well. We thus hypothesize that a manipulation of negativity and disgust, for example (Briesemeister et al., 2011b; Ponz et al., 2013a; Silva et al., 2012), would lead to comparable results.

Since the hierarchical model remains mute with respect to the second major affective dimension, affective arousal, the stimulus set used in the present study was controlled for its influence. Previous research highlights, however, that the N1 and other early ERP components are sensitive to arousal manipulations (Hofmann et al., 2009; Scott et al., 2009), which raises the question of the relationship between discrete emotions and arousal. Initial studies comparing the predictive power of both models for visual word processing indicate that they account for merely the same variance, with slight advantages for discrete emotions, suggesting that arousal should have no effect beyond a discrete emotion manipulation (Briesemeister et al., 2011b; Briesemeister, Hofmann, Kuchinke & Jacobs, 2012). Taken together with the rigorously controlled stimulus material (see Table 4.1), we are confident that the present results indeed document the impact of happiness, not arousal. Future research should however investigate possible interactions of discrete emotions (i.e. happiness) and arousal, thereby explicitly addressing their role in early

(Hofmann et al., 2009) and late processing stages (Olofsson, Nordin, Sequeira & Polich, 2008).

In summary, the present study found clear evidence in support of Panksepp's hierarchy of emotion processing levels in both behavioral and electrophysiological word recognition data. The effects reported here, in particular the observed behavioral interactions between the discrete and the dimensional affective information in the stimulus set and the specific sequentiality of the ERPs, cannot easily be explained in terms of the traditional discrete emotion or affective dimension theories alone. We believe that unifying frameworks like Panksepp’s hierarchy of emotion processing are promising starting points to bridge the gap between these theories – that still denote the need for further experimental examinations of the dynamics and the interactions predicted by current models describing emotional effects within and beyond visual word recognition research.

Dissociation of Happiness and Positivity

Chapter 05

A slightly different version of this chapter has previously been published as:
Briesemeister, B. B., Kuchinke, L., Jacobs, A.M. & Braun, M. (2014b). Emotions in reading: Dissociation of happiness and positivity. Cognitive, Affective, and Behavioral Neuroscience, DOI: 10.3758/s13415-014-0327-2

Abstract

The hierarchical emotion model proposed by Panksepp (1998) predicts that affective processing relies on three functionally and neuroanatomically distinct levels: engaging subcortical networks (primary level), the limbic system (secondary level), and the neocortex (tertiary level). The present fMRI study manipulated happiness and positivity assumed to rely on secondary and tertiary level processes, respectively, to test these assumptions in a word recognition task. In accordance with the model predictions, evidence for a double-dissociation was found in the brain activation pattern: Secondary level processes engaged parts of the limbic system, specifically right hemispheric amygdala. Tertiary level processes, in contrast, relied predominantly on frontal neocortical structures such as the left inferior frontal and medial frontal gyri. These results are interpreted as support for Panksepps model and as an indicator of a semantic foundation of affective dimensions.

Introduction

Even though considerable recent research on human affective processing relies on neuroimaging and electrophysiological evidence (Fritsch & Kuchinke, 2013; Satpute et al., 2013; Wilson-Mendenhall et al., 2013), most theories do not explicitly specify how and where exactly emotions are represented within the human brain (Lindquist, Wager, Kober, Bliss-Moreau & Barrett, 2012). One of only few notable exceptions is the hierarchical emotion theory proposed by Panksepp (1998, 2012), which generalizes evidence derived from electrical stimulation studies in animals to all mammalian species and thus allows for neuroanatomically precise predictions. For example, Panksepp (2007a) was among the first to suggest that the traditionally opposing concepts of discrete emotions, which describe emotions as a limited set of functionally distinct categories, and affective dimensions, which describe emotions as fluctuating states within two- or more dimensional spaces, are not alternatives, but refer to different affective processing levels within a neuroanatomically distinguishable three-level hierarchy. At the primary process-level, seven distinct emotional systems can be inferred from animal research. SEEKING, RAGE, LUST, PLAY, FEAR, PANIC and CARE are considered to be hardwired, unconditioned emotion processes that originate in emotion specific subcortical circuits within the periaqueductal gray (PAG) and the lower limbic system meant to provide fixed-action patterns that “allow organisms to face key environmental challenges with little need for individual learning” (cf. Panksepp, 2012, p.7). Satpute et al. (2013) recently demonstrated that the PAG, a core structure within the FEAR network known to be responsible for freezing and flight behavior in animals, is also involved in the processing of highly aversive images in humans. However, it is very difficult to non-invasively study unconditioned primary process-level emotions in humans, given that the involved structures are often very small (~10x6x3mm or approximately six standard voxels in case of the PAG) and adjacent to the cerebral aqueduct, which can cause magnetic inhomogeneities (Panksepp, 2012; Satpute et al., 2013). This is why researchers typically rely on secondary process-level conditioned affective processes. Affective conditioning (e.g., fear conditioning, LeDoux, 2000) relies on the pairing of unconditioned affective stimuli (primary process-level emotions) and the resulting unconditioned response to previously neutral stimuli. In case of word recognition, for example, Fritsch and Kuchinke (2013) demonstrated that the pairing of meaningless letter strings (pseudowords) with highly aversive images results in a conditioned ERP effect on the N1 component (~100ms) which strongly resembles early

ERP effects known from implicit affective word processing (Citron, 2012, see Bayer et al., 2012 for a more detailed discussion on early ERP effects and conditioning). According to Panksepp, tertiary process-level emotions, finally, rely on phylogenetically younger neocortical prefrontal brain structures and reflect higher order categorization, reorganization, and appraisal processes. Discrete emotions are shaped by sociocultural demands and clustered “into constellations of positive and negative affect“ (cf. Panksepp, 2006b, p. 22). Following this hierarchical theory of emotion, affective dimensions are derived from more basal discrete emotions, which requires more complex empirical tests.

Wilson-Mendenhall et al. (2013) asked their participants to immerse themselves in written scenarios meant to induce feelings of fear, happiness, and sadness and then to judge the resulting affective experience, while recording the associated brain activity with fMRI. The scenarios were constructed to elicit both positive and negative feelings for each discrete emotion category, i.e. they were “describing the pleasant fear of thrill seeking, the pleasant sadness of nostalgia, and the unpleasant happiness of unshared success “ (Wilson-Mendenhall et al., 2013, p.948) as well as prototypical happiness, fear, and sadness scenarios. Discrete emotions and affective dimensions were thus manipulated within one single experiment. The analyses revealed that participants’ subjective valence judgments were correlated with activity in the orbitofrontal cortex (see also Lewis et al., 2007) both within and across discrete emotion categories, while arousal judgments correlated with activity within the left amygdala. Wilson-Mendenhall et al. (2013) discuss these findings as evidence for a two-dimensional core affect, i.e. valence and arousal, underlying all affective experiences. Following the assumptions of the hierarchical emotion theory, however, valence judgments that correlate with orbitofrontal activations rely on higher-order evaluations and thus processing at the cortico-frontal tertiary process-level (Panksepp, 2007a). The amygdala, in contrast, is assumed to be a primary process-level structure, but with amygdala subregions discussed to be involved in different emotion systems (see Table 1 in Panksepp, 2001; also Wilson-Mendenhall et al., 2013). Of note is that amygdala is also often found active during fear conditioning (e.g. Duvarci, Popa & Paré, 2011; Maren, Phan & Liberzon, 2013; Phillips & LeDoux, 1992), thus it is also likely to be active in secondary process-level conditioned responses.

Recent evidence supporting the hierarchical emotion theory comes from an ERP study, where participants were presented with affective words in a LDT (Briesemeister, Kuchinke & Jacobs, 2014a). Word lists ‘high’ or ‘low’ in normative discrete emotion measures of happiness, and ‘neutral’ or ‘positive’ on the valence dimension (positivity) were orthogonally manipulated. This allowed to study the temporal signature of secondary (happiness) and tertiary (positivity) process-level brain responses. The happiness manipulation affected the very early N1 component around 100ms after stimulus onset, which is known to be sensitive to affective conditioning (Fritsch & Kuchinke, 2013). The positivity manipulation, in contrast, affected the late N400 component and the late positive complex (LPC), both of which are discussed to reflect explicit affective evaluation following word identification (Citron, 2012). No interaction between positivity and happiness was observed. These brain-electrical data thus strongly support Panksepp’s theory, given that happiness words assumed to primarily activate the secondary process-level affect an ERP component that precedes those affected by positivity words, which are assumed to primarily activate the tertiary process-level. Moreover, the processes that are discussed to underlie these specific ERP components, that is initial attentional resource allocation (N1), prolonged lexico-semantic processing (N400), and especially higher-order evaluation (LPC, see Citron, 2012), are also well in line with the model, given that Panksepp (2012) locates affective driven cognitive processes (N400, LPC) at the tertiary process-level.

An alternative, complementary approach for differentiating between secondary and tertiary process-levels is to focus on the involved brain structures rather than the temporal dynamics, in particular as Panksepp (1998; 2012) makes very precise neuroanatomic predictions. This is the goal of the present study which means to replicate and extend the results of Briesemeister et al. (2014a), using fMRI instead of ERPs. Based on Panksepp’s hierarchical emotion theory, we derived the following hypotheses:

Recent studies suggest that the processing of single affective words relies on emotion networks in the brain, such as the anterior and posterior cingulate cortex, the medial temporal lobe including hippocampus and parahippocampal gyrus, the amygdala, and the orbitofrontal cortex (Citron, 2012; Herbert et al., 2009; Kuchinke et al., 2005; Lewis et al., 2007; Nakic et al., 2006; Ponz et al., 2013a; Schlochtermeier et al., 2013). Work by Ponz et al. (2013a), for example, has shown that the insula cortex, which is strongly related to disgust processing (Wicker et al., 2003), is also involved in reading disgust related words. The authors interpreted this finding in terms of neural re-use (Anderson, 2010; Herbert et al., 2009), suggesting that phylogenetically younger processes such as reading rely at least partially on already existing old emotion processing regions, e.g., the limbic system (see also Bohrn et al., 2012; Jacobs, 2011; 2014). An fMRI replication of Briesemeister et al.’s ERP results (2014) is thus expected to reveal distinct activations within emotion-processing networks: secondary process-level emotions should rely on limbic brain structures, while tertiary process-level emotions should engage prefrontal brain regions. Previous work has already shown that discrete emotion words explain specific variance during lexical processing even when the stimulus material is controlled with respect to affective dimensions (Briesemeister et al., 2011b; 2014a; Silva et al., 2012; Weigand et al., 2013a), indicating separable underlying processes. Assuming that discrete emotion words indeed induce conditioned responses that mainly access the secondary process-level, a happiness manipulation as described in Briesemeister et al. (2014a) should, according to Panksepp (2001, Table 2), relate to the PLAY system. The primary process-level circuitry underlying PLAY consists of the parafascicular and posterior thalamic nuclei, the somatosensory cortex, the hippocampus, and the dorsal PAG (Panksepp, 1998; 2001), but as already mentioned, Panksepp (2012) and Satpute et al. (2013) agree that the primary process-level is difficult to access using fMRI. Moreover, it is unknown to what extent the primary process-level is accessed by conditioned affective stimuli, e.g. emotional words. The secondary process-level, in contrast, which can be accessed during word recognition tasks and the use of (conditioned) discrete emotion words, is not necessarily specific for a single primary process-level emotion, but predicted to rely on activation of the cerebellum, the temporal lobe, the amygdala, the lateral hypothalamus, as well as the cingulate cortex in the context of PLAY (see Panksepp, 1998, p. 291). Thus, greater activity within this PLAY network was expected for words high in happiness compared to words low in happiness. As regards the processing of valence along the positivity dimension (e.g., Briesemeister et al., 2012), which is expected to primarily access the tertiary process-level within the hierarchical emotion theory, greater activation with increasing positivity was expected to be observed in higher-order neocortical brain regions such as the orbitofrontal and medial frontal cortices (Lewis et al., 2007; Panksepp, 2007a; Schlochtermeier et al., 2013).

Methods

Participants

A total of twenty right-handed native German speakers (8 male, mean age = 23, SD = 2.7, range 19-35) were recruited at the Freie Universität Berlin. They had normal or corrected-to-normal vision and reported no known neurological condition or psychiatric illness. Prior to the experiment, participants gave written informed consent in accordance with guidelines set by the Charité ethics committee at Freie Universität Berlin. Participants were compensated with 15 EUR for participation.

Stimuli

Following Briesemeister et al. (2014a), 120 German 4-to-8-letter nouns and an equal number of nonwords were presented in a 2(happiness)*2(positivity) within-subject design with 30 items per cell. In order to investigate the specific contribution of discrete emotions and affective dimensions to affective word recognition, the present study relied on two published affective norm databases, the BAWL-R (Võ et al., 2009) and its discrete emotion extension, the DENN-BAWL (Briesemeister et al., 2011a). The BAWL-R provides rating-based affective norms for affective valence (7-point Likert scale, ranging from negative [-3] to positive [3]) and arousal (5-point Likert scale, ranging from low [1] to high arousing [5]) for almost 3,000 German words. Given that positivity judgments and BAWL-R's valence ratings are highly correlated (Briesemeister et al., 2012), words with BAWL-R scores between -0.7 and 0.7 were defined as being neu and words with valence scores above 1 were defined as being pos, thus covering the entire positivity spectrum. DENN-BAWL norms were used to additionally classify words as either being strongly related to happiness or not, with lowHap words having DENN-BAWL happiness scores below 2.6 and highHap words having scores above 2.6. The rational behind that was that the DENN-BAWL norms indicate the extent to which a single word is related to one of five specific discrete emotion categories, with high scores indicating a strong relation. The stimuli were selected aiming at a maximum manipulation of both variables. The resulting four orthogonal conditions (lowHap+neu, e.g. "HUHN", engl. "CHICKEN; lowHap+pos, e.g. "PRIVILEG", engl. "PRIVILEGE"; highHap+neu, e.g. "SATIRE", engl. "SATIRE"; highHap+pos, e.g. "EKSTASE", engl. "ECSTASY") showed uncorrelated happiness and valence scores (r=0.09), indicating that lowHap+pos words are perceived as being positive but not related to the discrete emotion happiness, that highHap+neu words are related to happiness but not perceived as being positive, and so on. For statistical details about the stimulus set see Table 5.1. Mean levels of arousal, imageability, (log-)frequency per million, bigram frequency, orthographic neighborhood size, frequency of orthographic neighbors, frequency of higher frequent orthographic neighbors, and the mean number of letters, syllables, phonemes and higher frequency orthographic neighbors were controlled using ANOVAs (all F's < 1, see Table 5.1). Moreover, all control variables were matched for the highHap versus lowHap and for the neu versus pos contrasts as verified by means of pairwise t-tests (all t's < 1). A list containing all words can be found in the supplementary materials. The 120 pronounceable but meaningless nonwords, matched to the words on number of letters and syllables (t's < 1), were taken from Briesemeister et al., (2014) as well. In addition, 30 filler items in form of five pound signs ('#####') were included, meant to increase the signal-to-noise ratio of the fMRI paradigm.

Table 5.1: Descriptive statistics for the stimulus set and the behavioral responses

	lowHap+neu	**lowHap+pos**	**highHap+neu**	**highHap+pos**	**F-value**	**p-value**
Happiness	2.3 (0.2)	2.4 (0.1)	2.9 (0.2)	2.9 (0.2)	74.760	< 0.001
Positivity	0.5 (0.2)	1.3 (0.2)	0.5 (0.2)	1.4 (0.2)	142.052	< 0.001
Log frequency	2.3 (2.1)	1.8 (1.9)	1.8 (1.4)	2.2 (1.7)	0.747	0.526
Letters	6.1 (1.4)	6.2 (1.2)	6.1 (1.4)	5.9 (1.2)	0.358	0.783
Syllables	2.0 (0.7)	2.1 (0.5)	2.1 (0.8)	2.0 (0.6)	0.287	0.834
Phonemes	5.5 (1.3)	5.7 (1.3)	5.4 (1.4)	5.3 (1.2)	0.721	0.541
Arousal	2.4 (0.3)	2.5 (0.6)	2.6 (0.6)	2.5 (0.8)	0.572	0.634
Imageability	4.7 (1.3)	4.6 (1.5)	4.9 (1.4)	4.9 (1.5)	0.256	0.857
Bigram frequency	182953 (129198)	224222 (166890)	196547 (158145)	164361 (133714)	0.871	0.458
Ortho. neighbors (N)	1.7 (1.9)	2.2 (3.4)	1.2 (2.2)	1.2 (2.2)	0.915	0.436
Frequency of N	116.8 (317.7)	210.6 (568.6)	161.2 (463.2)	127.9 (524.7)	0.233	0.873
Higher frequent N (HN)	0.5 (1.4)	0.6 (1.2)	0.9 (1.6)	0.4 (1.3)	0.537	0.658
Frequency of HN	82.4 (295.0)	192.6 (533.7)	157.7 (456.2)	115.4 (505.7)	0.333	0.801
Response times	719 (64)	765 (76)	719 (63)	741 (61)		
Error rates	1.2(1.5)	1.6(1.4)	0.9(1.0)	1.3(1.2)		
	lowHap	highHap	NEU	POS		
Response times	742(85)	730(74)	719(61)	753(65)		
Error rates	1.4(1.3)	1.1(0.9)	1(0.8)	1.4(0.9)		

Stimulus characteristics, including experimental and control variables of the stimulus set, as well as mean response times and error rates.

Procedure

While inside the scanner, participants received written instructions to decide as fast and accurate as possible via button press whether they were presented with a correct German word (index finger) or a nonword (middle finger). Moreover, they were instructed to not press any button when presented with fillers. Ten practice trials (4 words, 4 nonwords, 2 fillers) that were not part of the stimulus set described above were used to familiarize the participants with the task prior to the actual experiment.

Stimuli were presented in an event-related design via goggles using presentation software (Neurobehavioral Systems, Inc.), which also recorded response times and accuracy data. Each trial began with the presentation of a fixation cross (+) in the center of the screen, which was presented for 2500ms on average (jitter: 2000-3000ms), followed by the stimulus (1500ms) at the exact same position. Stimuli were fully randomized without constraints for each subject individually and presented in white uppercase Arial letters on black background, font size 50. Responses were given through a button box held in the right hand. The start of the first trial was controlled by an external pulse from the scanner.

Finally, a 5min anatomical T1 scan was recorded after completion of the lexical decision task.

MRI data acquisition

Neuroimaging was performed at the Dahlem Institute for Neuroimaging of Emotion using a 3T Siemens (Erlangen, Germany) Trim Trio MRI scanner equipped with a 12-channel head coil. Earplugs and headphones were used to attenuate scanner noise and form fitting cushions were meant to prevent the participants head movements. Functional imaging was done in a single run with 545 whole-brain T2*weighted echoplanar images (EPI) recorded in ascending interleaved order (TR: 2000ms, TE: 30ms, 70° Flip Angle (FA), 37 slices, matrix: 64x64, field of view (FOV): 192mm, 3x3x3mm voxel size, no gap). High resolution T1*weighted anatomic reference images were acquired as a set of 176 continuous sagittal slices (TR: 1900ms, TE: 2.52ms, 9° FA, matrix: 256x256, FOV: 256mm, 1x1x1mm voxels).

Data preparation

Mean LDRTs were calculated for each condition and participant after exclusion of nonresponders, behavioral errors and outliers, which were defined as responses faster than 300ms or slower than 1500ms. ERRs were calculated as summed errors per condition and participant. Statistical analyses were computed using ANOVAs as implemented in SPSS 13.0 (SPSS Inc., USA) at an a-priori significance level of 0.05.

Neuroimaging raw data were preprocessed and analyzed using SPM 8 (Available: http://www.fil.ion.ucl.ac.uk/spm/, Accessed: 2012 February 27). The images were slice time corrected, realigned to the mean volume, unwarped, normalized to the standard EPI template provided by the Montreal Neurological Institute (MNI) with 3x3x3mm voxel sizes and then smoothed with an 8mm (FWHM) Gaussian kernel. For statistical analyses, an event-related General Linear Model (GLM) analysis time-locked to the stimulus onset was used. On the first level, seven predictors were included as regressors in the design and convolved with the canonical hemodynamic response function (HRF): The four word categories lowHap+neu, lowHap+pos, highHap+neu, and highHap+pos words, nonwords, fillers and trials excluded from behavioral analyses (i.e. non-responders, errors and outliers as defined above). On the second level, participants were treated as random effects and the four word categories were included in a 2 (happiness) x 2 (positivity) flexible factorial ANOVA. Main effects of positivity and happiness were analyzed with F-tests to test for main effects and possible interactions. Follow-up one-tailed t-tests were used to estimate the direction of the effects. To correct for multiple comparisons, peak voxel ($p < 0.001$) and cluster size thresholds ($k > 17$) were used, following an a-priori Monte Carlo simulation procedure proposed by Slotnick et al. (2003). To estimate the appropriate cluster threshold, 10,000 simulations were run with the corrected p value set at $p < 0.05$ in the whole brain analyses and a FWHM of 12. Only activation clusters that survived these thresholds ($p > 0.001$, $k > 17$) are reported.

Results

Behavioral results

A 2 (happiness) x 2 (positivity) repeated measures ANOVA revealed a significant main effect of positivity which was driven by faster responses for neu than for pos words (detailed descriptive statistics are presented in Table 5.1, inference statistics in Table 5.2). Moreover, the happiness*positivity interaction approached significance ($p = 0.053$, see Table 5.2). Planned pairwise comparisons between all conditions were calculated and revealed faster processing for neu words than for pos words within both, the lowHap and the highHap condition. In addition, highHap words were processed faster than lowHap words within the pos condition but not for neu words. These results are also depicted in Figure 5.1.

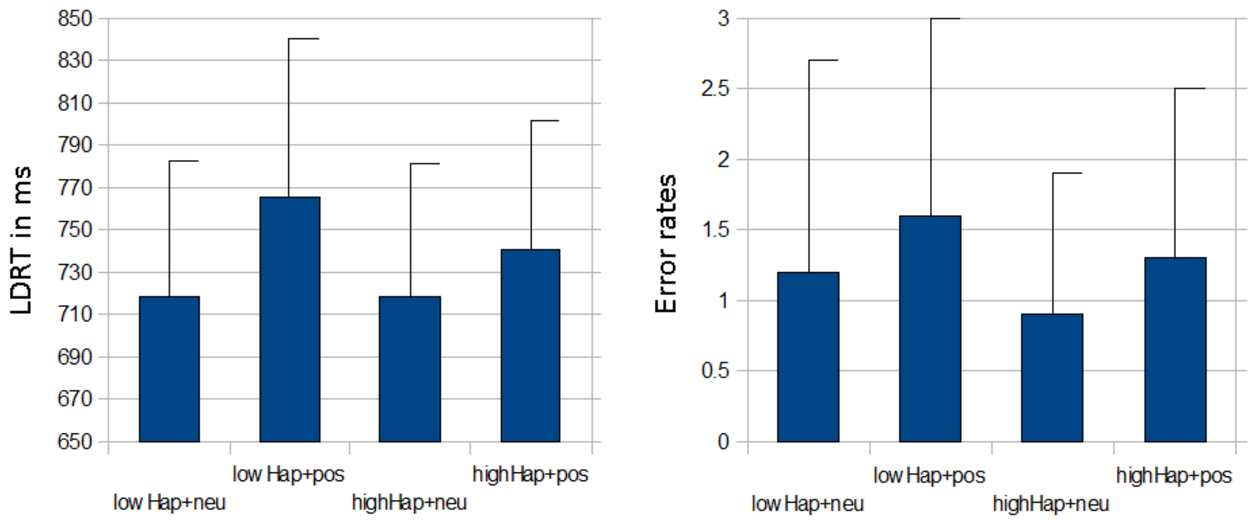

Figure 5.1: Behavioral lexical decision performance. Depicted are the mean lexical decision response times (LDRT) in ms and the mean summed error rates per condition. Error bars indicate one standard deviation.

Table 5.2: Inference statistics for the behavioral and fMRI data

Effect	F/t-value	p-value	η²-value
LDRT			
Main effect positivity	47.504	<0.001	0.714
Neu < Pos	6.868	<0.001	
Happiness*positivity interaction	4.258	0.053	0.183
lowHap+neu < lowHap+pos	6.297	<0.001	
highHap+neu < highHap+pos	2.844	0.010	
highHap+pos < lowHap+pos	2.200	0.040	
ERR			
Main effect positivity	6.538	0.019	0.256
neu > pos	2.557	0.019	

Anatomical location	L/R	BA	MNI coordinates			Voxel	T score
			x	y	z		
Main effect of positivity							
pos > neu							
Medial frontal gyrus	L	8	-3	26	43	112	5.59
Inferior frontal gyrus	L		-45	35	10	101	5.15
Inferior frontal gyrus	R	47	42	26	-8	24	4.12
neu > pos							
Precuneus	R	7	9	-58	40	74	4.46
Superior temporal gyrus	R	41	51	-19	7	48	4.27
Superior temporal gyrus	L	42	-63	-28	7	18	3.76
Main effect of happiness							
lowHap > highHap							
Cerebellum	R/L		6	-70	-38	71	4.95
	R/L		-3	-58	-14	85	4.72
Middle occipital gyrus	L		-51	-76	-5	33	4.78
Amygdala	R		21	2	-11	28	4.52

Anatomical locations for significant main effects of positivity and happiness at p < 0.001, corrected for cluster size (>17).

ERR (4% behavioral errors within the word material) were analyzed using a repeated measures ANOVA comprising the 2 x 2 within-subject factors happiness and positivity. A main effect of positivity was observed, based on fewer errors for neu than for pos words (see Table 5.2). No further effects reached significance. Given that ERR follow a binominal distribution (correct/incorrect), however, therefore violating several fundamental assumptions (see Jaeger, 2008), an additional mixed effects logistic regression was calculated using JMP Pro 11 (SAS Institute Inc., USA). Adding subjects and items as random effects to the model, the fixed effects (positivity, happiness, and their interaction) did not explain any variance. Thus, the ERR effect for positivity found in the ANOVA is not interpreted.

Neuroimaging results

A 2 (happiness) x 2 (positivity) flexible factorial ANOVA on the neuroimaging data revealed significant main effects for both factors, but no significant interaction between those. The happiness manipulation showed significant activation differences within the right amygdala, the cerebellum and the left middle occipital gyrus (BA 19). Follow-up one-tailed t-tests revealed that all these activation differences were related to increased differences for lowHap compared to highHap words. The effects and the corresponding effect sizes plotted as percentage signal change within the peak voxel are depicted in Figure 5.2 using the SPM toolbox rfxplot (Gläscher, 2009).

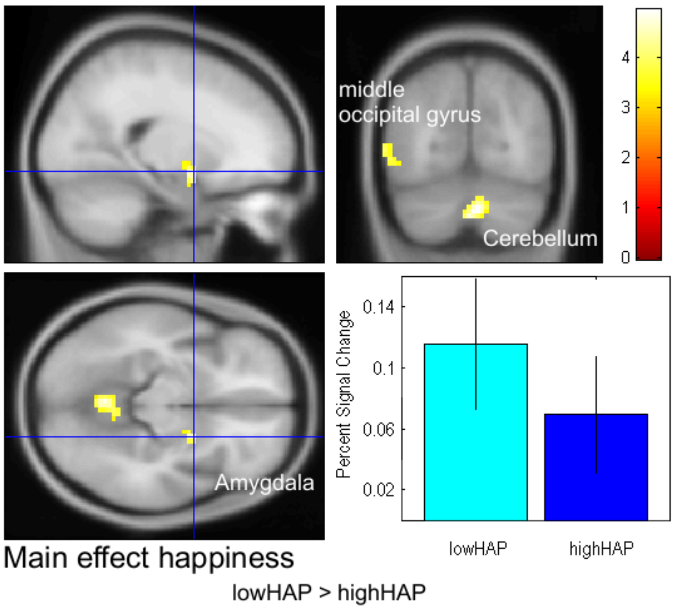

Figure 5.2: fMRI results for the happiness contrast (highHap versus lowHap). Depicted are structures that revealed significant differences for the happiness contrasts. Significant areas are labelled. The blue cross indicates the voxel that was used to extract the mean activation depicted in the bar chart.

The positivity manipulation affected activity within the precuneus (BA 7), mostly the left medial frontal gyrus (BA 8), the right superior temporal gyrus (BA 41) and two regions within the left inferior frontal gyrus. Direct contrasts between neu and pos words revealed increased activation differences for pos words within the medial frontal and the inferior frontal gyri. The reverse contrast revealed activation differences within the superior temporal gyrus and the precuneus, as also depicted in Figure 5.3. It should be noted that in the one-tailed contrasts, the inferior frontal gyrus effect for pos words and the superior temporal gyrus effect for neu words were significant in both hemispheres.

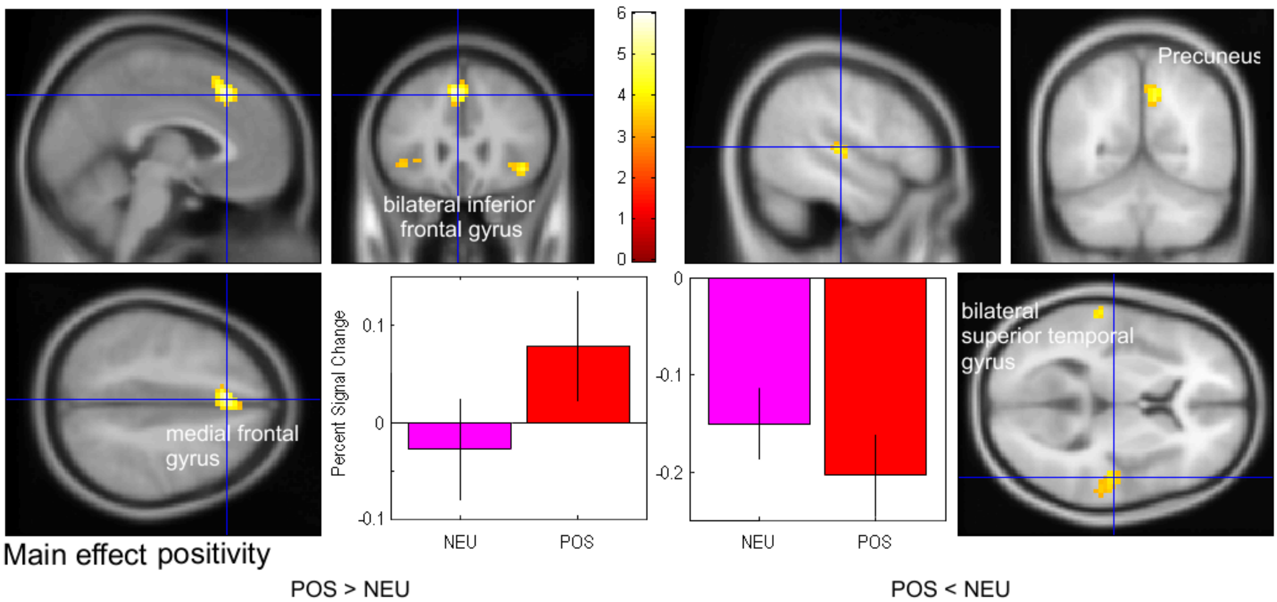

Figure 5.3: fMRI results for the positivity contrast (pos versus neu). Depicted are structures that revealed significant differences for the positivity contrasts, separated by direction. Significant areas are labelled. The blue cross indicates the voxel that was used to extract the mean activation depicted in the bar chart.

Discussion

The present study examined the three-leveled emotion processing hierarchy proposed by Panksepp (2012) and its applicability to affective word processing studies. Specifically, two hypotheses were being tested. Based on the neural re-use hypothesis (Anderson, 2010; Herbert et al., 2009) and the assumption that affectively conditioned stimuli like words access the secondary process-level within Panksepp's theory, we expected emotion networks like the anterior and posterior cingulate cortex, the medial temporal lobe including hippocampus and parahippocampal gyrus, the amygdala, and the orbitofrontal cortex to be involved in affective word recognition (Citron, 2012; Herbert et al., 2009; Lewis et al., 2007; Nakic et al., 2006; Ponz et al., 2013a; Schlochtermeier et al., 2013), despite the fact that the affective information is incidental to the task requirements (Kuchinke et al., 2005). In line with these predictions and replicating results by Nakic et al. (2006), the amygdala was found to be engaged during implicit affective processing in the present study.

Referring to Kuchinke et al. (2005), Nakic et al. (2006) discuss amygdala activity during emotion word recognition in relation to behavioral performance. According to these authors, amygdala activation indicates emotional salience and serves as input for regions that are relevant for the behavioral response, such as the medial orbito-frontal gyrus and the anterior cingulate cortex, which in turn facilitate the behavioral lexical decision response. This interpretation is based on a significant correlation between amygdala and anterior cingulate cortex activity in conditions which show enhanced word processing speed, namely for negative words in Nakic et al. (2009), and the absence of comparable effects when no facilitated processing is observed (e.g., for negative words in Kuchinke et al., 2005). The present results additionally contribute to this discussion about the role of the amygdala in affective word processing: As predicted by Nakic et al. (2009), affective information does not per se affect the amygdala, indicated by the absence of activation differences for the positivity contrast. Instead, amygdala activation was observed for the happiness contrast, which showed no behavioral main effect on LDRTs or ERRs and thus contradicts Nakic et al.'s (2009) assumptions. Given the theoretical framework of the present study, we interpret these results as suggesting that an explanation for activation differences within the amygdala, at least in the present study, must be related to the differentiation of discrete emotions versus affective dimensions.

Several recent studies show that manipulations along discrete emotion categories affect different word processing variance than manipulations along affective dimensions (Briesemeister et al., 2011a; 2011b; 2014a; Silva et al., 2012; Weigand et al., 2013a), suggesting that implicit processing of happiness and positivity reveals dissociable underlying networks. The results of Briesemeister et al. (2014a) already supported this hypothesis: An early N1 effect discussed to index early attentional resource allocation to affectively conditioned wordforms (Bayer et al., 2012) was found to separate high from low happiness words, while positivity affected the N400 and the LPC. Both components are associated with explicit affective evaluation. No interactions were observed. ERP studies are an excellent way to investigate such temporal sequences, and the results directly supported the hierarchical emotion model, but they are not suited to specify the neuroanatomical networks in a fine grained resolution. Panksepp (2012), however, makes precise neuroanatomical predictions, tested and supported in the present study by finding evidence for two non-overlapping networks that underlie the processing of happiness and positivity related words. Activity differences were observed within the amygdala, the cerebellum and the left middle occipital gyrus (see Table 5.2) when happiness words were processed. Most of these structures are part of Panksepp's (2012) secondary process-level network, supposed to underlie the processing of conditioned PLAY (and thus happiness) responses. Together with the happiness related N1 effect described in Briesemeister et al. (2014a), these results support a fundamental role of discrete emotions during (implicit) affective processing. The positivity manipulation, in contrast, revealed differences within structures strongly associated within the so-called reading network underlying semantic processing, i.e. within the superior temporal gyrus, the precuneus, and the medial and inferior frontal gyri (Binder & Desai, 2011; Binder, Desai, Graves & Conant, 2009; Kuchinke et al., 2005). According to Panksepp, the tertiary process-level “requires expansive neocortical tissues that permit lingustic-symbolic transformation” (Panksepp, 2005, p. 32), which can explain activation differences related to semantic processing for positive words. Again, these results extend Briesemeister et al.'s (2014a) finding of positivity related N400 and LPC effects discussed to represent semantic evaluation and integration processes (e.g., Kutas & Federmeier, 2011). Late ERP effects and neocortical reading network activity indicate that at least a minimum of lexico-semantic integration is about to happen when processing affective dimensions like positivity, given that secondary process-level discrete emotion differences are controlled. In line with this interpretation, the present study found positive words to be recognized significantly slower than neutral words, which is rather untypical (Briesemeister et al., 2012; Kuchinke et al., 2005) but replicates Briesemeister et al.s data (2014a). We interpret this effect as an index of increased processing demands when affective properties (secondary process-level) are controlled during implicit affect-based semantic categorization (tertiary process-level), which is most pronounced in the lowHap+pos condition (see Figure 5.1).

Replicating Briesemeister et al.’s finding (2014a), again no interaction between happiness and positivity was observed in the neuroimaging data. Even though the power in the present study might have been too low to detect interactive effects, the absence of an interaction is well in line with previous reports of independent proportions of variance explained by discrete emotion and affective dimension manipulations (Briesemeister et al., 2011a; 2011b; 2014a; Silva et al., 2012; Weigand et al., 2013a), and predicted by the hierarchical model (Panksepp, 2012). To the best of our knowledge, the present work is the first neuroimaging study trying to disentangle discrete emotion and affective dimension influences in word recognition. Previous studies focused exclusively on the contribution of affective dimensions such as valence (Kuchinke et al., 2005; Maddock, Garrett & Buonocore, 2003; Nakic et al., 2006) and their interaction with arousal (Citron et al., 2014), revealing activation differences within affective as well as within semantic reading networks. Kuchinke et al. (2005), for example, found positive words to engage the superior frontal and orbito-frontal gyri and negative words to engage the inferior frontal gyrus, which is in line with and in the same direction as the present tertiary process-level positivity effects in frontal regions. These results were interpreted as indexing explicit emotional memory functions. Additional activation differences when contrasting positive with neutral words were observed within the hippocampus, which is a secondary process-level structure in Panksepp's theory and was interpreted as indexing memory-emotion interactions by Kuchinke et al. (2005). Citron et al. (2014) report emotion related activation differences during lexical decisions within the cerebellum and the parahippocampus, both of which are part of the secondary process-level limbic pathways involved in cortical control of emotion. Further valence*arousal interaction effects were found within the superior temporal gyrus, which relates to the present positivity results and which the authors interpret as responsible for the decoding of affective content from visual information (Citron et al., 2014). They however also note that the superior temporal gyrus predominantly "is associated with semantic/conceptual categorisation as well as comprehension of coherent, comprehensible text" (Citron et al., 2014, p. 87), two functions explicitly associated with the tertiary process-level as predicted to underlie the processing of positive words in the present study. Studies like these caused Panksepp (2012) to ask for a clearer distinction of different affective processing levels to avoid causal misattributions, and the overall results presented here seem to support his view.

There are, however, also some unexpected effects. Both, the present study and its predecessor (Briesemeister et al., 2014a) show clearly independent effects of positivity and happiness in the neurophysiological data, while on a behavioral level a happiness*positivity interaction was observed. The hierarchical emotion model is a neurophysiological model of emotion and motivation, which is why precise predictions concerning more subtle behavioral effects, especially in the context of visual word recognition tests, are outside its scope. Even most word recognition and reading models do not consider affective influences, the extended multiple read-out model and the neurocognitive poetics models being notable exceptions (MROMe; Kuchinke, 2007; Jacobs, 2011; 2014; cf. also Hofmann & Jacobs, 2014). The MROMe predicts that affective information facilitates LDRTs at a pre-lexical level (see also Kissler & Herbert, 2013, for first empirical evidence), although it does not make a distinction between discrete emotions and affective dimensions, and therefore cannot account for possible interactions.

Moreover, the MROMe is not a neurophysiological model. Neural correlates are considered, but the focus is explicitly on processes of visual word recognition. The present results suggest that a combination and integration of behavioral and neurophysiological data is necessary to fully understand affective processing and visual word recognition alike, given that neurophysiologically separated structures can lead to interactive effects on the behavioral level. We assume that the different effect structure is caused by different time windows underlying behavioral and neurophysiological effects, but future theorizing should incorporate both levels of analysis to account for the existing complexities.

Despite their different foci, the MROMe and the hierarchical emotion model agree on the importance of the amygdala for affective processing (see also Siegle, Steinhauer, Thase, Stenger & Carter, 2002). It is well known that lesions within this structure can severely impair implicit affective processing (Anderson & Phelps, 2001), but its functional role is still a matter of debate. While the meta-analysis published by Sergerie, Chochol and Armony (2008) focuses on the amygdalae's role in affective processing, highlighting its sensibility for positive and negative stimuli alike, Pessoa and Adolphs (2010) argue that it is not affective content per se but biological significance that engages the amgydalae. In line with these hypotheses, previous affective word processing studies have found increased amygdala activity for both, negative (e.g. Nakic et al., 2006) and positive words (Schlochtermeier et al., 2013). The present data suggest an effect in the opposite direction, however, i.e. increased right amygdala activation for lowHap when compared with highHap words (see Figure 5.2). Whether this indicates that participants implicitly based their lexical decisions on highly emotional connotations of the stimulus material, which would make lowHap words unexpected and thus salient (Wright et al., 2001), can only be speculated. Given that the amygdala is known to engage in top-down influences to modulate (Pessoa & Adolphs, 2010) and enhance the detection of task relevant stimuli (Anderson & Phelps, 2001), this could explain why no LDRTs differences were found between lowHap and highHap words. Since Panksepp focuses his research on primary level-process emotions, he provides no detailed information on the amygdala’s functional role. In any case, our finding of increased amygdala activity for lowHap words is not predicted by the hierarchical emotion model.

It should also be noted that this work is based on positive word stimuli alone, which is a limiting factor in several ways. First of all, the hierarchical emotion model suggests altogether seven primary process-level emotions (i.e. the positive emotions PLAY, LUST, CARE, SEEKING and the negative emotions RAGE, PANIC, and FEAR). The present results so far relate to the PLAY system alone, but it would be interesting to see whether the three-leveled processing hierarchy, which is supposed to equally underlie all seven systems, applies for negative emotion words or words related to a different positive primary emotional system (e.g. LUST) as well. Such a replication attempt could provide evidence for a generalizability of the present findings.

Second and related to the focus on the positive end of the valence scale, it is possible that lowHap and neutral words were not perceived as being neutral/lowHap, but as slightly negative relative to the positive/highHap words. Recent research shows that even everyday “neutral” objects can readily be categorized into positive and negative groups when strong affective anchors are absent (Bar & Neta, 2007; Lebrecht, Bar, Barrett & Tarr, 2012). This suggests that the human brain calculates affective values not only depending on the presented stimulus, but also depending on earlier experiences and context (see also Barrett & Bar, 2009). The study by Bar & Neta (2007), for example, presented subjects with different everyday neutral objects, showing stronger activation within the amygdala and precuneus for disliked sharp versus liked curved contours. Knowing that the amygdala activation observed for lowHap words in the present study is discussed to be a crucial hub within the emotion processing network sensitive to highly affective information (Siegle et al. 2002) and knowing that the precuneus activation observed for neutral words in the present study has previously been associated with self-referential processing and episodic memory (Cavanna & Trimble, 2006, mainly triggered by negative stimuli, Blood, Zatorre, Bermudez & Evans, 1999), the focus on positive emotions in the present study might have caused neutral/lowHap words to be processed in brain regions associated with negative affect.

Third, Panksepp’s (2012) theory is an emotion theory, not a theory of affective word recognition. Word material was used in the present study because several recent studies suggest that words are an appropriate material to test complex affective relationships (Briesemeister et al., 2011b; 2014a; Silva et al., 2012; Weigand et al., 2013a), but the predictions tested here also apply to pictures, sounds or any other emotionally valenced stimulus. Keeping these limitations in mind and awaiting further research, we would like to propose that these first results provide initial support for Panksepp’s (2012) assumption of a dissociable affective processing hierarchy, with happiness words engaging mostly secondary process-level networks and positivity words relying on the semantic networks expected within the tertiary process-level.

General Discussion

Chapter 06

Since this research project started roughly five years ago, the strategic and theory driven investigation of affective word processing has made considerable progress – and the present manuscript means to further contribute to this development. Within this last half century, the initially dominating view that two affective dimensions, namely emotional valence and arousal (Barrett & Bliss-Moreau, 2009; Russell, 2003; 2005; 2009; Wundt, 1896), can account for the majority of emotion related effects in implicit and explicit word processing tasks has been challenged again and again. At least two arguments, both based on independent lines of research, can be put forward against the affective dimension view: Effects relying on affective dimension manipulations are not very stable, and other theoretical conceptions have proven to account for overall more affective word processing variance.

I will now discuss both arguments in detail, before I highlight how the present manuscript contributes to the present state of research.

Several attempts to replicate the Hofmann et al. (2009) study, which to the best of my knowledge was the first to experimentally document that the LDRT effect for emotionally negative words critically depends on a words level of affective arousal, with high arousing negative words being processed significantly faster than low arousing negative words, have failed. The multiple regression analyses published by Larsen et al. (2008) yet support the Hofmann et al. (2009) study, reporting several high level valence and arousal interactions, but a study published by Estes and Adelman (2008b), which relies on the exact same data as Larsen et al. (2008), convincingly argued for a categorical effect of valence that is independent of arousal. Kousta et al. (2009) reported no effect of arousal when valence was held constant and no emotion related response inhibition at all, which they explained with a sampling bias in the Estes and Adelman (2008b) and the Larsen et al. (2008) studies, given that both included only few neutral words in their analyses. Citron et al. (2014) found faster processing for low arousal positive than for high arousing positive words, which is opposed to Bayer et al. (2011), who reported the exact opposite pattern, and which is also contradicted by Recio et al. (2014), who reported no arousal effects for positive words at all. Kuperman, Estes, Brysbaert and Warriner (2014), finally, did the probably most exhaustive analysis of valence and arousal effects in lexical decision and naming tasks to date, found a linear main effect of valence that accounted for about 2% of the overall LDT variance and an inhibitory effect of affective arousal. This, again, contradicts almost all previous reports (e.g. Bayer et al., 2011; Larsen et al., 2008; Recio et al., 2014), given that arousal is normally documented to be a facilitating variable. The overall pattern of results when focusing on only two affective dimensions (valence, arousal) is thus very inconsistent and therefore not very convincing.

A second strong argument suggesting a limited focus of affective dimensions comes from the discrete emotion perspective. To the best of my knowledge, Parrott et al. (2005) pioneered in manipulating discrete emotions in affective word recognition research, reporting that participants who scored high on a trait anger scale were faster to detect anger related words than participants who scored low on a trait anger scale. No such effects were reported for sadness related words, which indicates that negative valence alone is not sufficient to explain the effect. Armstrong et al.'s (2009) investigation of processing differences for high and low contamination phobic participants are inconclusive, but a recent study by Silva et al. (2012) clearly documented the linear influence of disgust sensitivity on LDRT for disgust related words, by showing that highly disgust sensitive subjects needed longer to correctly identify disgust words than to identify neutral words while this effect was reversed for disgust insensitive subjects. Moreover, these effects were neither explained by subjectively experienced valence or arousal, nor by trait empathy used to measure general responsiveness to emotional material.

The initial discrete emotion studies reviewed above relied on behavioral responses alone. More recent work, however, also began to consider neurophysiological data to test the emotion specificity, which is central to the discrete emotion view. Ponz et al. (2013a), for example, showed that early ERP effects for disgust related words are most likely originating in the anterior insula cortex, which is known to be critically involved in the experience of disgust (Wicker et al., 2003). Weigand et al. (2013b) used repetitive transcranial magnetic stimulation (rTMS) over the right dorsolateral prefrontal cortex to inhibit the neural processes underlying an affective working memory task. They found increased accuracy for fear related but not anger related words, which can be interpreted as first evidence for an emotion specific causal involvement of the right dorsolateral prefrontal cortex in affective working memory tasks. Given that subjects rated fear related words as more negative than anger related words in their study, differences in perceived negative valence and thus within the affective dimension framework might also account for the Weigand et al. (2013b) effects. An additional rTMS study focusing on the specific contribution of left versus right dorsolateral prefrontal cortex eliminated this alternative explanation, however. Using a comparable stimulus set, Weigand et al. (2013a) showed that rTMS stimulation of the left versus right dorsolateral prefrontal cortex affected affective working memory performance for fear related words, but neither for neutral nor anger related words. This time, fear and anger related words were perceived as equally negative and equally arousing, according to the participants ratings.

The last five years have provided quite some evidence in support of the discrete emotion view when participants are asked to process affective words. The research presented in this manuscript replicated this work and further extends it in critical ways. Specifically, from my perspective, at least four major conclusions can be drawn from the studies presented in chapters 02 to 05, which I will now discuss in greater detail.

Conclusion 1: Discrete Emotions Affect LDT Variance even when Affective Dimensions are Controlled

The experiments done by Weigand et al. (2013a, 2013b) already provided initial evidence, and together with the LDT results described in chapter 02 and chapter 03 (see also Briesemeister et al., 2012), these studies on discrete emotions in affective word processing suggest that manipulations on discrete emotion variables affect different word processing variances than manipulations along affective dimensions. Moreover, discrete emotion effects while affective dimensions are kept constant can be documented not only using manipulations that affect different discrete emotion categories (see chapter 03), but also when only a single discrete emotion is manipulated (see chapter 02).

As discussed in detail in chapter 03, words that have strong affective connotations related to specific discrete emotions seem to affect the word recognition process in emotion specific ways, even when they do not differ in valence and arousal. Disgust words, for example, are not only processed slower than neutral words, which has been replicated several times by now (Armstrong et al., 2009; Briesemeister et al., 2012; Ponz et al., 2013a; Silva et al., 2012) but could also be explained within an affective dimension framework, given that neutral words are naturally less negative and less arousing than disgust words. The lexical decision study presented in chapter 02, however, also showed that disgust words are processes slower than arousal-controlled fear and anger words. This result additionally challenges the approach-avoidance explanation introduced by Citron (2011; see also Citron et al., 2013, 2014), assuming that both, disgust and fear words relate to avoidance motivation but demonstrably still differ in processing speed.

Assuming that the processing of affective words relies in one way or the other on the activation of emotion processing networks, as has been suggested (Barrett et al., 2007; Panksepp, 2008) and documented several times (Citron et al., 2014; Nakic et al., 2006; Ponz et al., 2013a), it should not be surprising that words related to different discrete emotions require different processing times. It is the core assumption of the discrete emotion view that different discrete emotions are *functionally distinct* (Ekman, 1992; Panksepp, 1998; Wundt, 1896). It is surprising, however, that a discrete emotion manipulation also affects LDRTs when valence and arousal are held constant while the manipulation is done within a single discrete emotion category, as described in detail in chapter 02. The finding that highHap words are processed faster than lowHap words even when they are equally positive and equally arousing can, in my opinion, be interpreted in at least two ways:

First, it is possible that discrete emotion norms are better suited than affective dimension norms (Eilola & Havelka, 2010; Redondo et al., 2007, Võ et al., 2006, 2009; Warriner, Kuperman & Brysbaert, 2013) to capture the variance that is manipulated within affective word recognition tasks because the discrete emotion view might be more suitable to explain the current effects than the affective dimension view. This is a pretty obvious and theoretically fundamental explanation, and although it was considered in chapter 02, it is challenged by the alternative second hypothesis, which suggests that discrete emotions and affective dimensions are related, but to a certain degree independent conceptions. As Wilson-Mendenhall et al. (2013, p. 948) already pointed out, discrete emotions are not always prototypical. There is the “pleasant fear of thrill seeking, the pleasant sadness of nostalgia, and the unpleasant happiness of unshared success”. Happiness is not always perceived positively, and not all positive emotions are labeled “happiness”. The data presented in chapters 04 and 05 strongly supports this latter view, as will be discussed in more detail in the following “Conclusion 3” paragraph.

In sum, the data presented in this manuscript documents that discrete emotion manipulations affect LDRTs and ERRs even when affective dimensions can not be held responsible. This conclusion alone should hopefully trigger further word processing research using discrete emotions, even more so when also considering the next conclusion.

Conclusion 2: Discrete Emotion Effects are Comparable in Different Languages

As already pointed out in the introduction to this thesis, affective word processing is investigated all over the world. Valence and arousal effects are well documented for German (Hofmann et al., 2009; Kanske & Kotz, 2007; Kissler & Koessler, 2010; Kuchinke et al., 2005; Palazova et al., 2011; Recio et al., 2014; Schacht & Sommer, 2009a; 2009b), English (Citron, 2011; Holtgraves & Felton, 2011; Kousta et al., 2009; Larsen et al., 2008; Scott et al., 2009, 2014; Siegle et al., 2001; Yap & Seow, 2014), Spanish (Carretié et al., 2008; Hinojosa et al., 2010), and French languages (Mohr et al., 2005; Naccache et al., 2005; Stip, Lecours, Chertkow, Elie & O'Connor, 1994), and soon affective norms will be available for Polish language as well (Riegel et al., 2014). There is no reason why similarly comparable results in different languages should not be expected for the discrete emotion view as well.

In fact, again assuming that discrete emotion word processing relies on affective networks (Ponz et al., 2013a; Briesemeister et al., 2014b), it is a crucial assumption of many discrete emotion theories that discrete emotion systems do not differ across human cultures (Ekman & Friesen, 1971) or even mammalian species (Panksepp, 1998). It is thus not surprising that discrete emotion effects on affective word recognition have been documented in English (Armstrong et al., 2009; Briesemeister et al., 2011b; 2012; Parrott et al., 2005), German (Briesemeister et al., 2011a; 2011b; 2014a; 2014b) and French alike (Silva et al., 2012; Ponz et al., 2013a). Moreover, the directions of these effects seem to be relatively stable across languages. Armstrong et al. (2009) were the first to indicate that disgust words seem to require more processing time than neutral words, using an English stimulus set. This effect was then replicated by Briesemeister et al. (2011b as described in chapter 03) in German and by a group of French scientists, who not only replicated the effect but also highlighted its underlying neurophysiological processes (Ponz et al., 2013a) and its relation to personal traits such as disgust sensitivity and empathy (Silva et al., 2012). While enhanced processing for positive words is the best replicated effect in the affective dimension view on word recognition tasks (see chapter 01), generally inhibitory but sensitivity dependent processing of disgust words is the best replicated effect within the discrete emotion view.

Language comparisons for discrete emotions other than disgust are done less frequently, but are for example documented in chapter 03. Here, a lexical decision experiment with German words revealed slower and less accurate processing of disgust words when compared with fear words, which are processed less accurate than anger related words. A comparable response pattern was also observed in a multiple regression analysis on English data from the ELP (Balota et al., 2007). Happiness words, which are the primary focus of the present research (chapters 02, 04 and 05), are also known to be processed faster than neutral words in both, German (Briesemeister et al., 2011a; 2014a; 2014b) and English (Briesemeister et al., 2011b; Parrott et a., 2005). Taken together, these data indicate that words related to specific discrete emotions indeed produce comparable effects irrespective of the language at hand – even though the data basis is, of course, much smaller than for the affective dimension perspective.

Conclusion 3: Discrete Emotions and Affective Dimensions are Complementary

The probably most surprising and most important result within this thesis is based on the data described in chapters 04 and 05. Traditionally, the discrete emotion perspective and the affective dimension perspective were seen as opposing views on the same research subject, (human) emotions that is. Several studies provided evidence for or against the one or the other (Reisenzein, 1994; Vytal & Hamann, 2010; Wilson-Mendenhall et al., 2013), leading to long discussions about the appropriateness of both theoretical positions (e.g. Barrett, 2006; Barrett et al., 2007; Izard, 2007; Ortony & Turner, 1990; Panksepp, 2007a; Scarantino & Griffiths, 2011).

The basic problem with most studies that contrast the two perspectives probably is that experiments like for example those described in chapter 02 and chapter 03 were designed to actually select a “winner”. Experimental designs are chosen to test the discrete emotion perspective *versus* the affective dimension perspective, given that they were and still are considered as opposing frameworks. Maybe, a more nuanced and more data driven theorizing as well as the acceptance of convincing evidence of both sides (e.g. Satpute et al., 2013; Wilson-Mendenhall et al., 2013) will lead to the idea that both perspectives could actually be combined within a single emotion theory (e.g. Panksepp, 2012; Russell, 2005). The use of neurophysiological variables and methods, which has become standard in emotion research over the years, might also have contributed to this theoretical evolution. Wilson-Mendenhall et al. (2013), for example, found convincing evidence that activity within the orbitofrontal cortex correlated with subjective valence judgements independent of whether the stimulus valence was manipulated within a single or between different discrete emotion categories, while at the same time the study from Satpute et al. (2013), coming at least in parts from the same group of researchers, presented convincing evidence that discrete emotion specific brain structures found in animal research (Panksepp, 1998; 2012) show comparably emotion specific effects in humans.

To the best of my knowledge, the experiments described in detail in chapters 04 and 05 are the very first affective word processing experiments that manipulated discrete emotions and affective dimensions at the same time. Based on the previous studies which reported that discrete emotion manipulations affect LDRTs and ERRs even when variables like valence and arousal are held constant (see chapters 02 and 03, but also Weigand et al., 2013a; 2013b), the finding of facilitated processing for happiness words should not be surprising. It has not been shown until now, however, that affective dimensions like positivity (Briesemeister et al., 2012) also affect word processing when discrete emotion variables are controlled, which suggests that discrete emotion and affective dimension variables describe possibly overlapping but also largely independent variances. Discrete emotions and affective dimensions are hence complementary, not opposing.

Further support for this interpretation comes from the neurophysiological data presented in chapters 04 and 05, where again no interactions between happiness and positivity were found. The early N1 effect evident for highHap versus lowHap words, for example, precedes any positivity related effect. Temporo-spatially, it also strongly resembles the N1 effect found by Fritsch & Kuchinke (2013), who used an affective conditioning paradigm where nonwords were paired with emotionally arousing pictures to investigate the functional meaning of affective word recognition ERP effects. These results were interpreted as evidence that discrete emotion effects like those for happiness words rely on affective conditioning. Effects for affective dimensions such as positivity, in contrast, modulated the N400 and the LPC, two components that are traditionally associated with higher order, often semantic processing (Foti et al., 2009; Kanske & Kotz, 2007; Kutas & Federmeier, 2011). This is well in line with Panksepps (2012) hierarchical theory, which is why further neuroanatomical predictions were tested – and confirmed – in the study described in chapter 05. Here, the happiness manipulation affected activity within the limbic system, namely the right amygdala, which according to Panksepp (1998) is a critical hub within the secondary process-level. Positivity words, in contrast, mainly modulate activity within the inferior frontal gyri, which are part of the tertiary process-level. Based on these data, the hierarchical model proposed by Panksepp (1998; 2012) seems to be the best candidate to explain the documented LDT effects, which indicates that the model also applies to affective word processing.

Having introduced the Panksepp (2012) model as a possible new point of reference for affective word processing and having shown empirically that the model can explain variance that is assumed to be error variance otherwise, the next step would be to look into the literature and search for further already existing but independent evidence for specific model predictions. Westbury, Keith, Briesemeister, Hofmann & Jacobs (in press), for example, showed that the co-occurence between a given word and words used as discrete emotion labels in emotion theories can be used to predict human valence judgements. This means that a word is perceived as more positive the more often it co-occurs with the word “PLAY”, for example. This finding nicely illustrates the two principles tested in the experiments described in chapter 04 and 05, namely affective conditioning as underlying the secondary process-level and evaluative judgements as underlying the tertiary process-level. Westbury et al. (in press) demonstrated that affective word processing effects, which normally rely on human affect rating data (Briesemeister et al.; 2011a; 2012; Eilola & Havelka, 2010; Redondo et al., 2007, Stevensen et al., 2007a; Võ et al., 2006, 2009; Warriner, Kuperman & Brysbaert, 2013), can be simulated using not human ratings but co-occurence similarities to words that label discrete emotion categories. Given that co-occurences are a measure for association strength between words and thus – in a way – one possible operationalization of affective conditioning, this result is well in line with the secondary process-level in Panksepps (2012) hierarchical model. Moreover, the idea that human valence and arousal judgements (i.e. affective dimensions) can be predicted based on the words co-occurence to discrete emotion labels strongly resembles the tertiary process-level function, where secondary process-level emotions are being clustered into broader categories. This is a line of research where I expect rapid progress within the next couple of years, given that a) affective conditioning has been identified as a core principle underlying affective word processing effects (Barrett et al., 2007; Fritsch & Kuchinke, 2013), b) many language related effects rely on co-occurences (Hofmann & Jacobs, 2014; Westbury et al., 2013), and c) conditioned responses can be operationalized in many different ways. Another example comes from Kuchinke, Krause, Fritsch & Briesemeister (2014), who showed that early ERP effects for affective words depend on the subjects familiarity with the word font. Words written in novel, unfamiliar fonts, that is word forms that have not been associated with emotionally arousing context before and thus might require additional cognitive effort to be semantically decoded, showed no early ERP effects on the P1 or N1 components, but a significant effect on the late positive potential (LPP). Familiar word forms, in contrast, additionally affected the P1 component, which might indicate that later semantically driven emotion effects on the tertiary process-level do not depend on familiarity and learning as strongly as the secondary process-level does. This, again, is predicted by Panksepp's hierarchical model (1998; 2012).

Further support can be expected when focusing on the diversity of emotional systems implemented by Panksepp (2012). The data presented within this manuscript mostly relies on positive happiness-related words and thus the PLAY system. The model suggests, however, the existence of altogether seven emotion systems, namely PLAY, LUST, CARE, SEEKING, RAGE, FEAR and PANIC. All of these emotion systems should affect affective word processing in different ways.

The study described in chapter 03 already provides initial evidence that anger words, which should be related to the RAGE system, are processed differently than fear words, even though a more detailed focus on the neurophysiological processes would be necessary to make more reliable statement. The same holds true for sadness related words (see chapter 03 and Briesemeister et al., 2012), which can probably be assigned to the PANIC system. LUST, CARE and SEEKING, however, have bot been implemented in any of the experiments within this thesis but are predicted to affect word processing within the hierarchical emotion framework presented here. This prediction is supported in a recent study by Stevenson et al. (2011), which suggested that an emotion category that considers sexually connoted words (i.e. words related to the LUST system) would help to explain otherwise unaccounted variance. In a factor analysis on different human word rating data, four major underlying factors could be identified. These were labeled “happy”, “disgusting”, “basic aversive” and “sexual”, the latter factor being totally independent of all other discrete emotion or affective dimension variables at hand. Based on their analyses, Stevenson et al. (2011, p. 59) conclude that “the addition of sexually specific emotions to basic emotion theories is justified and needed to account fully for emotional responses”. Moreover, valence and arousal ratings were not predictive of any of the four factors, supporting the model prediction that tertiary level-process affective dimensions rely upon secondary level-process conditioned discrete emotions (Westbury et al., in press), while inferences in the reverse direction are not informative. The Stevenson et al. (2011) data directly supports the conclusion that discrete emotions and affective dimensions are complementary and best combined in a temporo-spatially hierarchical model as suggested by Panksepp (2012).

The only finding presented so far that seems to be inconsistent with Panksepp's (2012) hierarchical model is the now often replicated inhibitory effect for disgust related words (chapter 03, Briesemeister et al., 2012; Briesemeister, Montant, Ziegler, Braun & Jacobs, 2013; Ponz et al., 2013a; Silva et al., 2012), given that disgust is not considered in Panksepps (2012) hierarchical model and given that disgust is not related to any of the seven emotion systems described in Panksepp (1998). In fact, there is a long debate on whether or not disgust should be considered one of the primary process-level emotional systems. Most of the criteria that Panksepp uses to define a primary process-level emotion system also apply to disgust (Toronchuk & Ellis, 2007a), the neuronal structures underlying disgust, namely the anterior insula cortices, have been identified (Wicker et al., 2003) and it is very likely that they are causally involvement in disgust processing (e.g. Ponz et al., 2013b). Toronchuk and Ellis (2007a; 2007b) thus initially suggested that disgust should be considered the eighth primary emotion system within the hierarchical model, which was disagreed by Panksepp (2007b). In his words, “disgust is clearly a basic sensory/interoceptive affect […], and a socially constructed moral emotion […], but perhaps it is a category error to classify disgust as a basic *emotion*” (Panksepp, 2007b, p. 1819, highlights as in the original reference). In their response, Toronchuk and Ellis (2007b, p. 1829) clarify that their proposal of DISGUST should not be misunderstood as a “distaste system”, but as a multisensory antagonist to the unspecific SEEKING system proposed by Panksepp (1998). This nicely mirrors the functional interdependence of the PANIC/CARE systems as proposed by Panksepp (1998) and resembles the functional architecture proposed within the Zurich model of social motivation by Norbert Bischof (1989, see also Schönbrodt, Unkelbach & Spinathm 2009 for a short English introduction).

Here, tedium of a familiar social object is functionally contrasted with curiosity for new social objects, which strongly resembles the functional architecture proposed to underlie the DISGUST/SEEKING dichotomy as suggested by Toronchuk & Ellis (2007a; 2007b).

In sum, the application of the hierarchical emotion model (Panksepp, 1998; 2012) seems to be well suited to explain why discrete emotions and affective dimensions independently affect affective word processing, and it additionally predicts previously unexpected effects for new emotion categories (e.g. LUST, see Stevenson et al., 2011). More research is needed to clarify the functional role of disgust within the hierarchical emotion model framework, but I am confident that future research using the affective word processing paradigm will further contribute to this discussion, which brings me to the final conclusion of this thesis.

Conclusion 4: Affective Word Recognition is Suited to Test Theories of Emotion

Within this manuscript, I initially introduced affective word processing as a branch of science that searched for emotion related effects rather than focusing on testable emotion theories (see chapter 01). It seemed like these early days were focused more on explaining variance within standard reading paradigms rather than aiming at a deeper understanding of how affective networks and reading networks might interact. Since these initial studies, much has changed, however.

The present manuscript is part of a richer literature which uses affective word processing paradigms such as the LDT to test specific hypotheses derived from published theories of emotion. It is therefore following the tradition of Larsen et al. (2008) and Hofmann et al. (2009), who documented that affective valence should be complemented by emotional arousal based on dimensional theories like the Core Affect model (Russell, 2003; 2005). Following the evaluative space model (Cacioppo & Berntson, 1994; Norman et al., 2011), lexical decision data from Briesemeister et al. (2012) suggests that positivity and negativity are not the endpoints of a bipolar valence scale but independent dimensions that under certain circumstances affect word recognition in different ways. Citron (2011) introduced the approach and avoidance framework from Davidson (1998) into the affective word recognition literature and showed that stimulus conditions with conflicting approach and avoidance motivations, that is high arousing positive and low arousing negative words, are indeed processed slower than conditions with congruent motivational tendencies (Citron et al., 2013; 2014).

The present work, finally, demonstrates that the discrete emotion perspective can additionally add to the affective word processing literature (chapters 02 and 03) and that the hierarchical emotion model proposed by Panksepp (1998; 2012) can predict and explain independent effects for discrete emotions and affective dimensions that are not being accounted for by any other emotion theory I know. Together with its predecessors, the present work thus demonstrates that affective word processing is suited to test between different theories of emotion and establishes the LDT as a standard paradigm in emotion research (e.g. Briesemeister et al., 2011a; 2011b; 2012; 2014a; 2014b; Citron, 2011; Citron et al., 2013; 2014). Even though the exact relationship between language and emotion remains a matter of debate, with contextual learning (Barrett et al., 2007, supported by Fritsch & Kuchinke, 2013; Kuchinke et al., 2014; Silva et al., 2012) and neural re-use (Anderson et al., 2010, supported by Ponz et al., 2013a) being discussed as possible explanations, future emotion research will likely reveal further information.

Initial evidence already points at a causal involvement of emotion structures in affective word processing (Ponz et al., 2013b).

Limitations and Future Directions

I will conclude this manuscript with a discussion of some limitations, as well as with some perspectives and suggestions for future research that should extend the present work and challenge some of my conclusions. First of all, the hypothesis that affective processing relies on a three leveled hierarchy, which has been demonstrated with positive, happiness-related words in chapters 04 and 05, should of course be replicated with positive words related to different primary process-level emotions, such as LUST (Stevenson et al., 2011), and with negative words. As already mentioned in chapter 05, the basic hierarchical structure with a primary, a secondary and a tertiary process-level should be observable irrespective of the emotion category that is being tested – and also independently of the affective stimulus material at hand, that is. Importantly, these studies would require the application of EEG or even fMRI measurements to ensure that LDRT differences are related to the respective processing level, based on the predictions in Panksepp (1998).

A more complex analysis of the EEG and fMRI data presented in chapters 04 and 05 would additionally allow to investigate the functional connections and interactions suggested by the hierarchical emotion model. Dynamic causal modeling as implemented in SPM, for example, would allow to test for correlations between secondary and tertiary process-level structures and therefore contribute to the functional understanding. These analyses, in fact, would already be possible based on the existing data and might help to identify the language-emotion link proposed by the Panksepp-Jakobson hypothesis (Jacobs et al., 2014).

Future studies should, secondly, of course be based on reliable stimulus norms. While norms for valence and arousal are available in numerous languages by now (Eilola & Havelka, 2010; Redondo et al., 2007, Riegel et al., 2014; Võ et al., 2006, 2009; Warriner et al., 2013), providing good tools for this line of research, norms for discrete emotions (Briesemeister et al., 2011a; Stevenson et al., 2007a) are so far published only for German and English. Although being confident that this will change in the near future, considering that discrete emotion effects are also published with French words, for example (Ponz et al., 2013a; Silva et al., 2012), and knowing that a Polish version of the DENN-BAWL is already in preparation (Wierzba et al., in prep.), I would also suggest to consider norm lists that are based on the seven primary process-level emotions PLAY, CARE, LUST, SEEKING, RAGE, FEAR and PANIC (Panksepp, 1998). If the affective word processing literature will continue to test and confirm the hypotheses from the hierarchical emotion model, more reliable stimulus material well be required than is currently available – even though co-occurence models might help to objectively quantify the affective value by then (Thagard & Schröder, 2014) without being dependent on subjective human ratings (Westbury et al., in press).

This brings me to my final outlook, namely the role of co-occurences in affective word processing. As already indicated above, co-occurence statistics are a measure of how often a given word occurs in the context of a second word, which is interpreted as an index for the semantic association of the two (Hofmann & Jacobs, 2014). Assuming that a single word like “joy” or “disgust” can be used as a prototype, as a label for an emotionally and thus functionally distinct context (Thagard & Schröder, 2014), then the co-occurence distance from that word to a theoretically grounded emotion word should indicate whether this word is emotionally charged or not. As demonstrated by Westbury et al. (in press), co-occurence measures indeed seem to predict human affective rating data and therefore might also account for affective word processing effects. Based on the assumptions of the hierarchical emotion model, affective co-occurence statistics could be interpreted as an index for the secondary process-level association strength between a given word and a primary process-level emotion system, which means that co-occurences to discrete emotion words, especially to those that are prototypical for the seven emotions systems, should predict early ERP effects and activation within upper limbic secondary process-level structures (Panksepp, 1998), such as the amygdala (see chapter 05). Moreover, using co-occurence based affective statistics to generate broader valence and arousal dimensions, as also demonstrated by Westbury et al. (in press), should affect later lexico-semantic ERP components such as the N400 and frontal and prefrontal brain structures such as the inferior frontal cortex (see chapter 06, but also Hofmann & Jacobs, 2014).

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