Electrophysiological Correlates of the Drift Diffusion Model in Visual Word Recognition

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Abstract: This study was designed to explore the electrophysiological correlates of the diffusion models drift rate parameter in cognitive decision making. Eighty-two participants completed a lexical decision task while their stimulus-dependent event-related potentials (ERP) and theta frequency band power were measured. A mass univariate approach was applied to examine the timeline at which correlations were evident. Individual differences in drift rate parameter and condition-wise within-subject differences in drift rates for word emotionality and item repetition were found to be related to amplitude differences in the late positive complex (LPC). No relations to theta frequency band power changes were obtained. The drift rate parameter captures information accumulation of noisy evidence, while LPC amplitudes are discussed to reflect the strength of a memory trace. While these results point to a common underlying cognitive mechanism to explain drift rates and LPC modulation, they also provide a new angle on the timeline of visual word processing following word identification. Further confirmations of the results are needed to approve the LPC as neurophysiological marker of information accumulation. *Hum Brain Mapp* 38:5616–5627, 2017. © 2017 Wiley Periodicals, Inc.

Key words: drift diffusion model; lexical decision; ERP; emotion; mass univariate approach

INTRODUCTION

Model-based neuroscience has attracted huge interest in recent years, as it is expected to bridge the gap between neuroscientific measurements and the underlying multifaceted cognitive architectures [Barber and Kutas, 2007;

Forstmann et al., 2016; Ratcliff et al., 2016]. For example, some recent studies in visual word recognition and sentence processing implemented computational models to examine and predict components of the event-related potentials (ERPs) [Brouwer et al., 2016; Frank et al., 2015; Laszlo and Armstrong, 2014; Laszlo and Plaut, 2012; Rabovsky et al., 2016; Rabovsky and McRae, 2014]. A related example of model-based neuroscience concerns modeling the decision process in two-choice reaction time tasks. The drift diffusion model (DDM) has been successfully implemented to model decision processes for a variety of different research questions in perceptual decision making (Ratcliff and McKoon, 2008). It has been proven as valuable tool in investigating emotion effects (Pe et al., 2013), individual response patterns (Froehlich et al., 2016), and effects of aging (Ratcliff et al., 2004b) or psychological illness (White et al., 2009, 2010). By computing DDMs, the decision process is modeled with up to seven parameters that facilitate theory building and testing (Ratcliff et al., 2004a; Voss et al., 2013). While behavioral studies on DDM parameters are numerous, their neuropsychological

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Figure 1.

An illustration of decision processes in the lexical decision task modeled by a DDM. Boundary parameter a indexes response caution and z the starting point which is here set to half of the boundary parameter a as both responses are equally often required. Dashed arrows index drift rates that vary in steepness and leads either to a word or to a nonword response. Corresponding response time distributions are shown in the form of histograms at the response boundaries. The decision process is flanked by encoding processes and motor responses that are summarized under the nondecision time parameter t_0 and are here indicated by grey areas.

correlates are less extensively studied especially in cognitive decision making. However, to fully comprehend the decision process, it is essential to also cover its neural foundation. Neural correlates of DDM parameters have been studied in simple perceptual decision making (Philastides et al., 2006; van Vugt et al., 2012), but unfortunately, the field is lacking studies with comparable examinations for higher order cognitive decision making. This study seeks to contribute to this discussion by examining electrophysiological correlates of DDM parameters in response to decisions made in visual word recognition.

The DDM (Fig. 1) assumes that decisions are made by accumulating noisy evidence over time until one of two thresholds is reached and the corresponding decision is made. Thereby, each individuals' response time (RT) distributions are taken into account. Boundary parameter " a " indicates how far both thresholds are apart from each other. Larger values indicate that thresholds are further apart leading on average to longer decision times that are less prone to errors, compared to models where the boundary parameter is small, indexing that thresholds are relatively close. When participants have no information about upcoming trials, the boundary parameter cannot be adapted in a stimulus-dependent manner and is, therefore, estimated over all stimulus categories. Decision bias parameter z indicates an initial shift toward one of the responses, for which then less information needs to be accumulated to reach the threshold (Voss et al., 2015). When both responses occur equally, often the decision

process is assumed to start at half of the boundary parameter a , thereby indexing no bias toward either response. Visual encoding processes and execution of motor responses are captured in nondecision time parameter " t_0 ." When equivalent encoding demands and response method are required for each stimulus, the parameter is as well expected to be similar for different stimulus categories (Voss et al., 2013). Drift rate parameter " v " is the most studied DDM parameter that captures information accumulation of noisy evidence until a boundary is reached (Voss et al., 2013). Stimulus and task qualities are, for example, known to affect the drift rate parameter, resulting in different mean slopes of the decision process (Ratcliff et al., 2004a). As the drift rate parameter is stimulus dependent, it is modeled separately for each stimulus category. Together, these parameters of the model govern the speed of responses and which choices are made for different stimulus categories.

Characteristics of the DDM are well mirrored in single-cell firing rates. Smith and Ratcliff (2004) describe that single-cell firing rates in monkeys oculomotor areas were connected to the accumulation of noisy evidence in eye movement decision tasks. They describe that a build-up in neuronal firing rate was related to a central process of target selection and not an antecedent for a specific response, similar to what is modeled in the DDM where information accumulation occurs for both options until it is ultimately driven to one of the thresholds. Higher stimulus quality in these studies was associated with rapidly rising neuronal firing rates and fast RTs (e.g., Roitman and Shadlen, 2002), which is mirrored in the DDMs drift rates. In DDMs, higher stimulus quality is mirrored in larger drift rates that index enhanced information accumulation and are related to faster response times (Ratcliff, 2002). Furthermore, RTs were predicted by the time it took for the firing rate to reach a threshold value which is how the DDM is built. Once the drift rate reaches a threshold, the response is initiated.

Therefore, the findings on single-cell neuronal firing rates appear to be closely tied to the DDM but cannot be easily studied in humans. A less invasive approach of studying neuronal correlates of the DDM is the use of electroencephalography (EEG) respectively ERPs which was first presented by Philastides et al. (2006). In their study on perceptual decision making, a late ERP component emerged which was found to be related to information accumulation as evident in a correlation of the components' magnitude and estimated drift rate parameters. Temporally relating this ERP component to estimated nondecision times revealed that it peaked directly after stimulus encoding and its peaks' latency increased with task difficulty. Van Vugt et al. (2012) used a different approach by investigating the relation of information accumulation to increases in oscillatory power bands of the EEG in a perceptual decision task. Thereby, they identified a ramp-like increase of theta band power from stimulus onset until the response was given, as best describing the data changes in the theta frequency band that

were related to information accumulation (the drift rate determines the slope of the ramp). Changes in theta frequency band oscillations have previously been discussed to indicate sustained attention and enhanced perception. In their study, van Vugt et al. (2012) particularly observed covariations of the magnitude of the slopes in the theta frequency range 500–100 ms before the response with participants' drift rates.

Studies that have related electrophysiological evidence to DDM parameters or, more specifically, to the stimulus-dependent drift rates, are rare and typically use simple perceptual decision tasks (Philiastides et al., 2006; van Vugt et al., 2012). Whether and how these findings extend to higher order cognitive decision processes have not been investigated sufficiently so far. To fill this gap, we use a correlative design to explore the electrophysiological manifestations of drift rate parameters in visual word recognition using the lexical decision task with 82 participants to establish a high statistical power. The lexical decision task is one of the most prominent paradigms in visual word recognition (e.g., Grainger and Jacobs, 1996) and is known to reflect bottom-up perceptual and top-down semantic and affective processing (Hofmann and Jacobs, 2014; Jacobs et al., 2015). The DDM framework has been successfully applied to assess behavioral aspects of the lexical decision task several previous times (Mueller and Kuchinke, 2016; Ratcliff et al., 2004a, 2004b; White et al., 2009, 2010). If the effects from perceptual decision making are transferable to more high-level cognitive decision making, we expect individual differences in evidence accumulation as represented by the drift rate parameters to be related to ERP amplitudes (Philiastides et al., 2006) and power values in the theta frequency band (van Vugt et al., 2012). However, the lack of studies in this field hinders the formulation of hypotheses regarding specific time windows of the appearance of these correlations. Therefore, we adapted a version of the mass univariate approach toolbox (Groppe et al., 2011) that allows the investigation of the averaged trials' entire time frame for correlations between EEG signal and drift rate parameters while controlling for multiple comparisons across all time points and EEG channels. In order to be able to temporally relate these findings to visual word processing, the onset of the lexicality effect (word vs nonword processing) will be investigated in the first step.

Condition-wise examinations of the drift rate parameter have revealed to also capture differences in stimulus quality, for example, in terms of differences in word emotionality (Mueller and Kuchinke, 2016). In the second step, this study simultaneously examined two aspects of stimulus quality in the lexical decision task: item repetition effects and emotionality. All stimuli were presented twice in two experimental blocks in this study. As item repetition is also known to affect RTs and ERPs in visual word recognition (Mendez-Bertolo et al., 2011; Simon et al., 2004), these repetition effects were assessed for their effects on drift rates and their electrophysiological correlates in

within-subject analyses. The effects of word emotionality were assessed in a similar manner. Taken together, this study presents the first attempt to use DDMs to link higher level cognitive processes to electrophysiological signatures both across individuals and within different aspects of word processing.

MATERIALS AND METHODS

Participants

The group of 82 participants (60 females) between 17 and 34 years of age ($M = 22.62$, $SD = 3.90$) was recruited via notices on bulletin boards at Ruhr University Bochum or via social media. Only participants who fulfilled the criteria of being right-handed, having normal or corrected-to-normal vision and not having a history of neurological disorders took part in the study and were rewarded either with course credit or with 15 € allowance. Written informed consent was obtained of all participants prior to the beginning of the experiments. The study was conducted in accordance with the Declaration of Helsinki and approved by the local ethics committee of the Faculty of Psychology at the Ruhr University Bochum. Data of 3 participants had to be excluded from analyses due to technical difficulties resulting in the loss of EEG data.

Stimuli, Apparatus, and Data Preparation

As in the study of Mueller and Kuchinke (2016), 75 German nouns (4–6 letters) that differed in their emotional category were taken from the DENN-BAWL database (Briesemeister et al., 2011a) and matched regarding their level of arousal, number of letters, syllables, phonemes, orthographic neighbors, word frequency, imageability, and averaged bigram frequencies.¹ The word material had previously been used by Briesemeister et al. [2011b, experiment 3] and consisted of 25 happy, 25 neutral, and 25 fear-related nouns (mean valence ratings (SDs): $M_{\text{happy}} = 1.9$ (0.5); $M_{\text{neutral}} = 0$ (0.3); $M_{\text{fear}} = -1.6$ (0.4)) which differed significantly ($F(2, 72) = 446.18$; $P < 0.001$, all pairwise comparisons $P_s < 0.001$). Nonwords were built by taking 75 different nouns of 4–6 letter lengths, where one or two letters were replaced by different letters resulting in meaningless but pronounceable nonwords. In total, the word material consisted of 150 letter strings that were each presented twice resulting in 300 trials.

Participants had to indicate via button press whether each presented letter string was a word or a nonword.

¹Matching results for happy, neutral, and fear conditions (means and P values): arousal (3.26, 3.36, 3.43; $P = 0.361$), number of letters (4.92, 4.96, 4.96; $P = 0.970$), syllables (1.76, 1.76, 1.72; $P = 0.949$), phonemes (4.48, 4.52, 4.40; $P = 0.892$), orthographic neighbors (2.16, 2.16, 2.56; $P = 0.823$), word frequency per million (18.8, 28.3, 26.0; $P = 0.804$), imageability (4.24, 4.46, 3.98; $P = 0.345$), and averaged bigram frequencies (178,338, 148,039, 201,658; $P = 0.352$).

Mapping of left and right buttons were switched for half of the participants. All letter strings were presented on a computer screen in upper case letters in font Arial size 80 pt using Presentation™ (neurobehavioral systems). Each trial started with the presentation of a fixation cross for a jittered amount of time between 350 and 450 ms, followed by a letter string in black font against a light grey background. After 400 ms, the letter strings were masked by an array of seven hashtags that stayed on screen for another 1100 ms. Participants were able to indicate their answer during the entire trial time from presentation of the word until the disappearance of the hashtags 1500 ms later. Once the answer was given, the hashtag mask decreased in length from seven to five hashtags, so that participants had a visual reassurance that their button press was recorded. After disappearance of the hashtags, a blank screen was shown for 200 ms before the next trial started. Participants were asked to respond as fast and accurately as possible. Before starting the experiment, participants completed 10 practice trials during which the instructor was available to them for questions. After 75, 150, and 225 trials, participants had a self-paced rest period. As stimuli were each shown twice, the trial order was pseudorandomized to make sure that each stimulus appeared once in the first 150 trials and once in the second 150 trials. In the instruction, participants were made aware that stimuli might appear more than once. In total, task completion took ~15–20 min.

For data analysis, RTs for correct responses were submitted to a low cutoff criterion at 250 ms. Upper boundaries were identified by adding the respective 3 standard deviations to each individuals mean response time for each category (happy, neutral, and fear-related words, nonwords). Error-free word RTs and error rates were submitted to a repeated measure analysis of variance with the factors presentation (first and second) and emotion as within-subjects factor comprising three levels (happy, neutral, and fear-related words).

After giving written informed consent, participants took part in a number of experiments that were not part of this research question and will be reported elsewhere. The here presented lexical decision task was the second of two tasks during which EEG was recorded. For this purpose, the EEG cap (EasyCap) was placed on each participants head and participants were seated in front of a 17" Dell computer screen where they completed the tasks. In between tasks, participants were always given the opportunity to rest for as long as they liked. In total participants stayed in the laboratory for about 120 min, including the time to wash and dry their hair.

EEG recordings

EEG recordings were obtained using Brain Vision Recorder (Brain Products, Munich, Germany) and took place in a dimly lit, sound- and light shielded room. EEG data were measured using the AC settings of an AC/DC

amplifier (BrainProducts) and Ag–AgCl electrodes (acti-Cap, BrainProducts) placed on an elastic cap (EasyCap BrainProducts) according to the international 10/20 system. Data were recorded from 27 scalp sites (F3, F4, Fz, FC1, FC2, FC5, FC6, FCz, C3, C4, Cz, CP1, CP2, CP5, CP6, P3, P4, P7, P8, Pz, PO3, PO4, PO7, PO8, O1, O2, Oz), referenced to the right mastoid and grounded to AFz. Additionally, to place an electrode on the left mastoid for later re-referencing, each participants' vertical electrooculogram (EOG) with electrodes above and below the right eye and horizontal EOG from two electrodes at the outer canthi were recorded resulting in the measurement of 32 electrodes. Impedances were kept below 5 k Ω and data were sampled at a rate of 500 Hz.

EEG data preprocessing

Recorded EEG data were preprocessed using Brain Vision Analyzer (BrainProducts). First, a 0.1 Hz low cutoff filter and a 40 Hz high cutoff filter were administered to electrophysiological data. Channels were referenced from the right mastoid to averaged right and left mastoids. Afterward, a manual raw data inspection was carried out to discard muscular artefacts and time slots during which participants took breaks. An ocular correction ICA implemented in Brain Vision Analyzer 2.0 (BrainProducts) using an Infomax algorithm was carried out to correct the data for eye movements. To make sure that no artefacts were left, an automatic raw data inspection was carried out maximally allowing amplitudes of ± 90 μ V. Segments of correct trials only were cut out 200 ms prior to stimulus onset until 800 ms after stimulus onset and baseline corrected to the prestimulus interval. These baseline corrected segments were then averaged across each category (words and nonwords). For subsequent analyses regarding the LPC, the late positive complex of the ERP, data were segmented for each presentation (first, second) and each emotion category (happy, neutral, fear) separately. An area export was carried out over all electrodes in the time window from 450 to 550 ms after stimulus onset according to the time window, where the EEG signal was observed to correlate with individual drift rates (see Results).

For analyses regarding the theta frequency band, power values between 4 and 8 Hz were extracted separately for words and nonwords from the segmented, baseline corrected, and averaged data using a Hilbert transformation in Brain Vision Analyzer.

The mass univariate approach toolbox (Groppe et al., 2011), which offers a way to explore a large number of data comparisons, was used to identify time points in the EEG signal where responses to words differed from responses to nonwords. Data of all electrodes and inspected time points were compared. The Benjamini and Hochberg procedure (Benjamini and Hochberg, 1995) which is implemented in the mass univariate approach toolbox was applied to control the rate of false discoveries. Thereby, α was corrected such that maximally 5% of the

TABLE I. Descriptive statistics of DDM parameters

	Mean	SD	range
a	1.12	0.22	0.70–1.90
t_0	0.53	0.07	0.40–0.73
st_0	0.24	0.09	0.08–0.46
v_{word}	3.26	0.68	1.93–4.83
v_{nonword}	–2.36	0.48	–1.22 to –3.47

a : boundary parameter indexing the width between thresholds; t_0 : nondecision time comprising decoding processes before the decision process and motoric processes of response execution; v_{word} and v_{nonword} indexing the rate of information accumulation for words and nonwords.

significant correlations were actually false discoveries. Corrected α values and the number of significant comparisons and the maximal number of false discoveries (5% of all significant comparisons) are reported. For this purpose, the not yet segmented data were exported from BrainVision Analyzer to Matlab (MathWorks) and further processed with EEGLab and ERPLab. More specifically, event lists were created for each participant and bin-based epochs were extracted analog to the segmentation reported before. Averaged ERPs were computed and participants' ERP data sets were then processed using the mass univariate approach toolbox. To investigate the dynamics of correlations between EEG signal and individual drift rate parameters of the DDM, we modified the mass univariate approach toolbox script. Correlations coefficients between the word related diffusion model's drift rate parameters and participants' EEG signals (ERPs and power in the theta frequency band) in response to words over time were computed for each time point and each EEG channel. t statistics for each correlation coefficient were transferred back to the standard mass univariate toolbox to be FDR controlled for multiple comparisons.

Diffusion model analysis

Adjusted RTs ($250 < \text{RT} < \text{mean RT} + 3 \text{ SD}$) and accuracy measures were submitted to diffusion model analyses. All diffusion models were run using fast-dm (Voss and Voss, 2007). Data were fitted using a maximum likelihood function.

To investigate the effect of lexicality, a first diffusion model was estimated with separate drift rates for words and nonwords only. All word responses independent of their actual emotion categories were mapped onto the upper boundary and nonword responses were mapped onto the lower boundary. For further within-subject analyses regarding the effects of stimulus repetition and word emotionality, a second DDM was run using fast-dm where drift rates varied for both presentations (first and second) and for different emotion conditions (happy, neutral, fear, nonwords), resulting in 8 estimated drift rates for this second DDM. For both DDMs boundary parameter a and

nondecision time t_0 were assumed to be equal for all trials as participants had no prior knowledge about any upcoming trial and required responses were similar (Ratcliff et al., 2004a; Voss et al., 2013). The starting point z was set to half of the boundary parameter a assuming an unbiased decision (Voss et al., 2015). Intertrial variabilities of starting points, nondecision times, and drift rate parameters were set to zero. Fast-dm additionally provides the possibility to model faster responses to one of the two boundaries in parameter d and it allows to model a percentage of contaminants (parameter p) but only for a very large number of trials. Both these parameters were set to zero as well. An alternative model with a varying intertrial variability of t_0 was estimated. For both models, Akaike information criteria (AIC values) were computed and compared showing that the model with varying st_0 outperformed the first model. For all 79 included data sets, AIC values were smaller for the model where st_0 allowed to vary. All subsequent analyses were based on the parameters of models with varying st_0 (Table I).

RESULTS

By applying the criteria of including only correct RTs lying between 250 ms and mean RT + 3 SD, 0.7% of the trials were excluded (mean upper outlier boundaries: happy words = 997 ms; neutral words = 1058 ms; fear-related words = 1100 ms; nonwords = 1132 ms).

Descriptive Statistics

Over all emotion categories, the mean response time for words was 666.29 ms (SD = 92.45) while the mean response time for nonwords was 743.47 (SD = 107.09). On average, 6.65% errors were made in response to words (SD = 3.5%) and 3.86% errors were made in response to nonwords (SD = 4.00%). Descriptive statistics of diffusion model parameters can be gathered from Table I.

Behavioral Data Analysis

Significant effects of emotion on behavioral data and on estimated drift rates and LPC amplitudes can be gathered from Figure 4.

Response Times

The repeated measures analysis of variance with the factors presentation (first, second) and word emotionality (happy, neutral, fear) revealed significant main effects of presentation $F(1, 78) = 67.33$; $P < 0.001$; partial $\eta^2 = 0.463$; $1 - \beta > 0.99$ and word emotionality $F(2, 156) = 98.17$; $P < 0.001$; partial $\eta^2 = 0.557$; $1 - \beta > 0.99$ but no significant interaction of both factors $F(2, 156) = 0.440$; $P = 0.645$; partial $\eta^2 = 0.006$; $1 - \beta = 0.12$. Post-hoc Bonferroni-corrected pairwise comparisons revealed that responses were faster

for the second ($M = 645.62$ ms; $SD = 87.55$) compared to the first presentation ($M = 692.39$ ms; $SD = 105.93$; $P < 0.001$). Responses to happy words ($M = 643.45$ ms; $SD = 89.97$) were faster compared to neutral ($M = 674.63$ ms; $SD = 95.83$), and slowest for fear-related words ($M = 688.94$ ms; $SD = 100.00$; all pairwise P s < 0.001).

Error rates

The repeated measures analysis of variance with the factors presentation (first, second) and word emotionality (happy, neutral, fear) again revealed significant main effects of presentation $F(1, 78) = 23.90$; $P < 0.001$; partial $\eta^2 = 0.235$; $1 - \beta > 0.99$ and word emotionality $F(2, 156) = 151.27$; $P < 0.001$; partial $\eta^2 = 0.660$; $1 - \beta > 0.99$ but no significant interaction of both $F(2, 156) = 0.86$; $P = 0.415$; partial $\eta^2 = 0.011$; $1 - \beta = 0.186$. Post-hoc Bonferroni-corrected pairwise comparisons revealed that more errors were made on the first ($M = 7.4\%$; $SD = 3.82\%$) compared to the second presentation ($M = 5.79\%$; $SD = 3.91\%$; $P < 0.001$). Additionally, more errors were made in response to fear-related words ($M = 12.63\%$; $SD = 6.54\%$) followed by neutral ($M = 4.68\%$; $SD = 4.22\%$), and least errors for happy words ($M = 2.56\%$; $SD = 2.62\%$; all P s < 0.001).

Lexicality Effect

Using the mass univariate approach toolbox, we identified the time point at which the ERP in response to words and nonwords started to differ. The analysis was carried out on all 27 scalp electrodes during the time window from 50 to 800 ms after stimulus onset corresponding to 376 time points and a total number of 10,152 comparisons. The Benjamini and Hochberg FDR control was applied identifying ± 2.2233 as critical t scores corresponding to a corrected alpha level of 0.029. Identified were 5968 significant differences while the upper bound of false discoveries was estimated at 298.4. The curves started to differ after 232 ms on electrode FCz. The effect was significant over all electrodes from 268 ms until 600 ms after stimulus onset (Fig. 2).

Correlation of Theta Band Power and Drift Rates

The correlation of the power in the theta frequency band and drift rate in response to words was investigated during the time window between 50 and 800 ms after stimulus onset corresponding to 376 time points. For 27 scalp electrodes and 79 participants, this resulted in 10,152 correlations. The Benjamini and Hochberg FDR correction was applied revealing no significant correlations between the two measurements.

Correlation of ERP Signal and Drift Rate

The correlation of the ERP signal and drift rate in response to words of all emotion categories as estimated by the first DDM was investigated during the time

window between 50 and 800 ms after stimulus onset corresponding to 376 time points. For 27 scalp electrodes and 79 participants, this resulted in 10,152 correlations. The Benjamini and Hochberg FDR correction was applied identifying ± 0.28 as critical levels of significant correlations. Identified were 2304 significant correlations and the upper bound of false discoveries was estimated at 115.2. First significant positive correlations were evident after 368 ms on electrode F4 building up to a cluster of significant positive correlations with more positive going ERP amplitude for individuals with higher drift rates 400 ms after stimulus onset on electrodes F3, F4, Fz, FC5, FC6, FC1, FC2, FCz, C3, C4, CP1, CP2, CP5, CP6, P3, Pz, P4, P7, P8, PO3, PO7, PO4, O1, Oz, and O2 (Fig. 2).

Further Analyses of Drift Rates and the LPC

As a correlation was evident of EEG amplitudes and individual drift rates in the LPC time window, further analyses were carried out regarding possible modulations due to stimulus repetition and word emotionality on a within-subject basis. For these analyses, results of the second DDM were analyzed which estimated separate drift rates for both repetitions and emotion categories. Word emotions effects of drift rates and LPC amplitudes can be gathered from Figure 4. Model fits are shown in Figure 3.

Drift rates were submitted to repeated measures analysis of variance with the factors presentation (first, second) and word emotionality (happy, neutral, fear). There was a significant main effect of presentation $F(1, 78) = 106.24$; $P < 0.001$; partial $\eta^2 = 0.577$; $1 - \beta > 0.99$ with larger drift rates for the second presentation ($M = 4.38$; $SD = 1.25$) compared to the first presentation of the items ($M = 3.07$; $SD = 0.67$). Additionally, there was a main effect of word emotionality $F(2, 156) = 238.32$; $P < 0.001$; partial $\eta^2 = 0.698$; $1 - \beta > 0.99$ with larger drift rates for happy words ($M = 4.82$; $SD = 1.25$) compared to neutral ($M = 3.70$; $SD = 0.90$) and fear-related words ($M = 2.66$; $SD = 0.83$). Bonferroni-corrected post-hoc comparisons revealed that all word emotion categories differed significantly from each other (P s < 0.001). Moreover, the interaction of presentation and word emotionality was significant $F(2, 156) = 16.44$; $P < 0.001$; partial $\eta^2 = 0.174$; $1 - \beta > 0.998$. Subsequent analyses on word emotionality for the different presentation times were conducted. There was a significant main effect of word emotionality for the first presentation $F(2, 156) = 154.31$; $P < 0.001$; partial $\eta^2 = 0.664$; $1 - \beta > 0.999$ with largest drift rates for happy ($M = 3.83$; $SD = 0.94$) compared to neutral ($M = 3.12$; $SD = 0.74$) and fear-related words ($M = 2.25$; $SD = 0.75$). All Bonferroni-corrected pairwise comparisons were significant (P s < 0.001). A repeated measures analysis of variance for word emotionality for the second presentation revealed again a main effect of word emotionality $F(2, 156) = 96.41$; $P < 0.001$; partial $\eta^2 = 0.553$; $1 - \beta > 0.999$ with largest drift rate for happy

Figure 2.

(A) Lexicality effect over time: colored boxes index time points for the corresponding electrode for which ERPs in response to words and nonwords differed significantly from each other (FDR-corrected). Color intensity indexes the strength of the t statistic. (B) ERPs in response to words and nonwords on electrode Pz. (C) Correlations of drift rates and EEG signal. Colored boxes index clusters of time points of FDR-corrected significant correlations (at $P < 0.05$). (D) Scatterplot of drift rates and ERP amplitudes on electrode Pz in the time window between 400

and 500 ms after stimulus onset. (E) Topography plots of the LPC in response to words between 400 and 500 ms after stimulus onset. (F) Topography of the lexicality effect (word LPC–nonword LPC) between 400 and 500 ms. (G) Topography of the difference in LPC amplitudes in response to words for participants with large versus small drift rates (based on a median split) between 400 and 500 ms. [Color figure can be viewed at wileyonlinelibrary.com]

($M = 5.81$; $SD = 2.14$) compared to neutral ($M = 4.28$; $SD = 1.39$) and fear-related words ($M = 3.07$; $SD = 1.13$). Again, all Bonferroni-corrected post-hoc comparisons were significant ($P_s < 0.001$).

Averaged amplitudes of all electrodes were analyzed for the time window of the LPC between 400 and 500 ms after stimulus onset using a repeated measures analysis of variance with the factor presentation (first, second) and the factor word emotionality (happy, neutral, fear). There was a significant main effect of presentation $F(1, 78) = 61.94$; $P < 0.001$; partial $\eta^2 = 0.443$; $1 - \beta > 0.99$ with larger amplitudes for the repetition ($M = 3.15$; $SD = 4.27$) compared to the first presentation of the items ($M = 1.52$; $SD = 4.05$). Additionally, there was a main effect of word emotionality $F(2, 156) = 56.02$; $P < 0.001$; partial $\eta^2 = 0.168$; $1 - \beta > 0.99$

with largest amplitudes for happy ($M = 2.99$; $SD = 0.437$) compared to neutral ($M = 2.06$; $SD = 4.03$) and fear-related words ($M = 1.95$; $SD = 4.17$). While Bonferroni-corrected pairwise comparisons revealed that happy words differed significantly from both other types of words ($P_s < 0.001$), there was no significant difference among neutral and fear-related words ($P > 0.99$). The interaction of presentation and word emotionality was also significant $F(2, 156) = 3.48$; $P = 0.035$; partial $\eta^2 = 0.043$; $1 - \beta > 0.629$. A subsequent analysis of variance with the factor word emotionality on first presentation revealed a main effect of word emotionality $F(2, 156) = 11.94$; $P < 0.001$; partial $\eta^2 = 0.133$; $1 - \beta > 0.993$. Bonferroni-corrected post-hoc comparisons revealed again largest amplitudes for happy ($M = 2.24$; $SD = 0.435$) compared to neutral ($M = 0.97$;

Figure 3.

The graphs show empirical (solid lines) and predicted (dashed lines) cumulative distribution functions (cdf) separately for the three emotion categories and presentation times (top row, first presentation; bottom row, second presentation). The y-axis shows the cumulative probability while the x-axis indicates the response time. Predicted cdfs were based on the estimated

diffusion model parameters. Predicted and empirical cdfs were computed for each participant separately and then averaged across all participants. Error responses are plotted in the negative spectrum of the x-axis while correct responses are plotted in the positive spectrum.

SD = 4.11) and fear-related words ($M = 1.35$; SD = 4.43) ($P < 0.005$) while neutral and fear-related words did not differ significantly from each other ($P = 0.404$). On second presentation, the main effect of word emotionality was again evident ($F(2, 156) = 8.66$; $P < 0.001$; partial $\eta^2 = 0.100$; $1 - \beta > 0.966$). However, post-hoc Bonferroni-corrected comparisons showed that amplitudes in response to happy

($M = 3.75$; SD = 4.75) and neutral words ($M = 3.15$; SD = 4.43) did not differ significantly anymore ($P = 0.145$) just as neutral and fear-related words ($M = 2.55$; SD = 4.36) did not differ significantly ($P = 0.105$). Only the difference between happy and fear-related words was significant ($P < 0.001$).

Additionally, behavioral measures and estimated drift rates were correlated with LPC amplitudes separately for

Figure 4.

The plots show means of RTs, error rates, drift rates, and LPC amplitudes separately for the three emotion categories. Solid lines indicate the values for the first presentation and dotted lines for the second presentation. Asterisks indicate significant differences between conditions. Note that for all outcome measures, there was a significant main effect of presentation that is not indicated here.

TABLE II. Correlations of drift rates, response times, and error rates with LPC amplitudes

		Drift rates	RTs	Error rates
1	Happy	0.291**	-0.441**	0.018
	Neutral	0.299**	-0.294**	-0.098
	Fear	0.379**	-0.307**	-0.334**
2	Happy	0.159	-0.436**	-0.033
	Neutral	0.368**	-0.479**	-0.102
	Fear	0.293**	-0.419**	-0.232*

Numbers in the first column indicate the presentation (first and second); ** indicates $P < 0.05$.

first and second presentation and the three emotion categories. Correlation results can be gathered from Table II.

DISCUSSION

This study represents an explorative approach to examine electrophysiological manifestations of the diffusion models drift rate parameter in a lexical decision task as an example for a task requiring higher order cognitive decision making. Integrating typical effects of lexicality, electrophysiological findings, and DDM parameters inform findings regarding the timeline of visual word recognition. An effect of lexicality was evident after about 250 ms which is within reported boundaries in the literature considering large variations mostly depending on word frequency of the stimulus material (Dambacher et al., 2006; Hauk et al., 2006; Kissler and Herbert, 2013; Sereno and Rayner, 2003). More positive going amplitudes were visible on all electrode sites for word compared to nonword stimuli. The peak of the lexicality effect was most evident in the time window of the late positive complex, the LPC, between 400 and 500 ms after stimulus onset. Therefore the timing of the obtained LPC lexicality effect which is assumed to indicate the point in time when words are fully identified through access to the mental lexicon, resembles a common finding (Braun et al. 2006; Citron, 2012; Hauk et al., 2006).

The first main result temporally ranks the electrophysiological correlates of the DDM drift rate parameter as an individual difference variable relative to this timeline of visual word processing. Participants with larger drift rates in response to word stimuli show more positive going amplitudes in a late ERP time window that based on its more posterior topography would best be described as resembling an LPC (e.g., Polich, 2007, Van Strien et al., 2007). This effect was visible from 398 ms after stimulus onset on and is thus clearly later than the point of lexical access evidenced by the main effect of lexicality. The LPC is often considered as a reflection of controlled and evaluative processing to “respond according to the task requirements” (Citron, 2012) and has been discussed to indicate the successful (re-)activation of a memory trace (e.g., Polich, 2007). The obtained positive correlations with the drift rate parameters in this study reveal that individual differences

between participants are reflected in amplitude differences in the LPC time window. The first, preliminary interpretation could point to enhanced evaluative processing following word identification and clearly before a response is made (on average ~666 ms) in participants with overall larger drift rates, that is, better information accumulation to separate the signal of word identity from its noisy distracting alternatives. Similarly, if the positive-going amplitudes of LPC reflect “good” reenactment of a memory trace, one could also argue that participants with lower drift rates reveal less positive and thus simply less well elaborated reactivation processes. Still, it should be emphasized that standard models of visual word recognition would assume that word identification has already taken place during these time periods when the drift rate parameter shows the highest correlations (e.g., Hauk, 2016; Hauk et al., 2006; Kissler and Herbert, 2013). A related interpretation is that this later ERP signature reflects differences in accumulated word evidence, which would become more pronounced as the decision unfolds. As an analogy, if two runners, one fast and one slow, were in a race, the separation between them would be small at the beginning of the race but continue to grow as the race unfolds. Similarly, with the evidence accumulation for lexical processing, the accumulated evidence for participants with higher drift rates would begin to separate from those with lower drift rates as the decision process unfolds. Thus the difference between them would be larger and more significant at a later time point than when the lexicality effect first appears.

To further elaborate these findings, a second within-subject analysis was carried out to also reveal the power (and dynamics) of condition-wise drift rate variations. Word repetition was shown to affect drift rates in that overall drift rates were larger when participants saw the word for the second time compared to the words’ first presentation. Larger drift rates index a better process of information accumulation, a steeper approach to the boundary to reach a decision (Ratcliff et al., 2004a). Participants knew that they would encounter words more than once and evidently were able to use the familiarity through repetition to reach a boundary quicker. As we have previously shown (Mueller and Kuchinke, 2016), drift rates were also influenced by word emotionality. This was evident in a main effect revealing largest drift rates for happy, followed by neutral and least pronounced drift rates in response to fear-related words. Breaking down the interaction of word repetition and word emotionality confirmed that for both presentations the same emotion effects were evident that were also apparent in the main effect of word emotionality but with larger effect sizes in the repetition. This result slightly differs from that in Mueller and Kuchinke (2016) using the very same stimulus material (without item repetition), where no significant difference in drift rates was obtained between the processing of neutral and fear-related words. The greater statistical power through the larger number of participants likely contributed to the more detailed finding. The pattern of largest drift rates in response to happy, followed by neutral and least pronounced drift rates in response to fear-related words was, nonetheless, the same

in both studies. A processing advantage for positive words is often reported in the emotion word recognition literature for response times and error rates (e.g., Briesemeister et al., 2011a; Hofmann et al., 2009; Kousta et al., 2009). As is also discussed in Mueller and Kuchinke (2016), the extended multiple read-out model (MROME) [Kuchinke, 2007], which is a computational model of the lexical decision task, assumes enhanced lexical activity for emotional words resulting in processing advantages. This overall facilitation, however, is mostly evident in implicit processing of happy words. Effects of automatic vigilance are additionally discussed to likely bind attentional resources on the processing of negative stimulus material (Estes and Adelman, 2008), resulting in slowed down processing of fear-related words. We believe that these processes contribute to the observed pattern of enhanced processing of happy words followed by neutral and last fear-related words (cf. Briesemeister et al., 2011b using the same stimulus material).

Results on modulations of LPC amplitudes by repetition and word emotionality mirrored those of drift rates. LPC amplitudes were increased in response to the words' second compared to their first presentations. Such LPC findings are consistently reported in the literature (cf. Rugg, 1985; Van Strien et al., 2005) and were taken as an index of the strength of a memory trace (Van Strien et al., 2007). Additionally, there was a main effect of word emotionality on LPC amplitudes with largest amplitudes in response to happy compared to neutral and least pronounced amplitudes in response to fear-related words. Breaking down the interaction of word presentation and word emotionality revealed that on the first presentation of the words, LPC amplitudes in response to happy words were significantly larger compared to amplitudes in response to neutral and fear-related words. On the repetition, LPC amplitudes in response to happy and neutral words did not differ significantly while the difference between happy and fear-related words remained significant. In emotion word recognition literature, larger LPC amplitudes to positive compared to neutral or negative words have been discussed to reflect stimulus evaluation and integration at late, semantic processing stages (Briesemeister et al., 2014; Citron, 2012; Kissler et al., 2009; Kissler and Herbert, 2013). Of note is that these studies sometimes fail to find LPC amplitude differences between neutral and negative words, which has been interpreted in terms of differences in the timing of emotional effects elicited by negative (or here fear-related) material that might be less evident in late processing stages (Kissler and Herbert, 2013).

In sum, descriptively, drift rate effects clearly mirrored the obtained LPC amplitude changes in the within-subject analyses. The reported correlations between drift rates and LPC amplitudes in Table II corroborate this impression and we believe this strong relationship between trait-like individual difference patterns and state-like condition effects in both drift rates and LPC modulation point to common underlying cognitive mechanism. As can be gathered from

Table II, correlations of LPC amplitudes and response times were also evident and even larger than correlations between drift rates and LPC amplitudes. To further examine this effect, we computed the partial correlation between LPC amplitudes following word stimuli and individual drift rate parameters controlled for the effect of response times. Correlations between LPC amplitudes and drift rates respectively RTs were of comparable size ($r = 0.436$ resp. $r = -0.434$). The partial correlation remained significant ($r = 0.299$; $P = 0.008$). Thus, drift rates explain up to 8.9% of the variance in average LPC amplitudes alone. As we have introduced above, response times mirror a mixture of underlying processes. Apparently, more than one of these processes was reflected in LPC amplitudes. Following our model-based analysis we are now able to conclude that LPC amplitudes mirror the process of information accumulation as evident from the correlational analyses. Other processes might be reflected by the LPC amplitudes as well and should be explored further in future studies. For now, the data let us state that information accumulation as represented by the drift rate parameter of the diffusion model is reflected in LPC amplitudes of the EEG signal.

Our findings best fit the interpretation of van Strien et al. (2007) of the LPC amplitude as an index of the strength of a memory trace. Information accumulation in the lexical decision task involves the process of identifying the letter string. If a memory entry of the letter string is found in the hypothetical mental lexicon (or not), the participant is able to compute a decision on the given item. A larger drift rate describes faster information accumulation, in which a higher quality of information is extracted from the stimulus (Ratcliff et al., 2004). These processes are electrophysiologically reflected in larger LPC amplitudes.

In addition to ERPs, the correlation of drift rates to power values in the theta frequency band was investigated. Contrary to van Vugt et al. (2012), we were not able to find any time window during which theta band power and drift rate correlated. Our deviating findings might be due to differences in statistical power, experimental paradigms, and/or their underlying processes (i.e., perceptual compared to cognitive decision making). The discrepancy might as well be due to methodological differences. Van Vugt et al. (2012) investigated the theta frequency band between 4 and 9 Hz while we defined the theta band as ranging from 4 to 8 Hz (Schacter, 1977). An upper boundary of 9 Hz borders to the alpha frequency band which is typically defined as having 8 Hz as lower boundary (Klimesch, 1999), and alpha frequency power might have compromised the theta frequency findings in van Vugt et al. (2012).

The information gained from DDM parameters and the drift rates electrophysiological correlates complete the timeline of word processing. Nondecision time was estimated to take up 525 ms on average. Assuming that roughly 100 ms are attributed to the motor response after a boundary is reached (Philiastides et al., 2006), leaves about 425 ms of

nondecision processes for the time before information accumulation starts to be evident in the EEG signal (assuming an additive process). During this time, the visual stimuli are decoded. 400 ms after stimulus onset, the correlation of drift rate and EEG signal starts to be evident. The mean response time for words was ~666 ms, which confirms the estimation of Philiastides et al. (2006) of the motor response taking about 100 ms. The correlation of drift rates and ERP amplitudes lasts until a boundary is reached (550 ms after stimulus onset) and is no longer evident once the motor response execution is initiated 100 ms prior to the response. Thereby, the end of the correlation marks the time point at which the boundary is reached which fits to the interpretation of the LPC amplitude as a marker of memory retrieval.

This proposed timeline can, however, not be postulated without any doubt. Only if more detailed information on the nondecision time parameter was available, that is, if it was possible to split it up into subprocesses that occur before information accumulation starts and processes that are related to the motor response after information accumulation has occurred, could we assure this timeline. Also the pattern of results on the influence of word emotionality was not identical for drift rates and LPC amplitudes. While for drift rates all emotion categories differed significantly from each other for both presentations, this was not true for LPC amplitudes even though the pattern looked similar. The LPC might therefore capture other processes additionally to information accumulation. Further confirmations of the results are needed to approve the LPC as neurophysiological marker of information accumulation in the lexical decision task and to investigate whether the LPC mirrors this process similarly well in other stimulus modalities, thereby extending the research agenda to further paradigms that capture cognitive decision making.

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