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The Effects of Perceptual Fluency on Emotional Word Recognition

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A thesis submitted in partial fulfillment of the requirements for the Master of Science degree in Psychology

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Abstract

To investigate if making a word harder to read attenuates emotional influences like valence and arousal, we used a sample of Warriner and colleagues' (2013) corpus with valence and arousal norms, a font manipulation from the perceptual fluency paradigm, and a word naming task. We found that, contrary to our hypotheses, emotional influences of words on RT were not attenuated in the disfluent condition; in fact, disfluency seemed to amplify the facilitative effects of high arousal. These results suggest that models of word recognition should consider the role that emotions play in recognition. They also provide limited support to models that emphasize the importance of perceptual features (e.g., Fritsch & Kuchinke, 2013) as well as the facilitative effect of high valence words (e.g., automatic vigilance), but, ultimately, do not fit into one specific theoretical framework. This study also represents the first application of perceptual fluency in emotional word recognition.

Keywords

Word Recognition, Reading, Emotion, Valence, Arousal, Fluency, Semantics

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Chapter 1

1 Introduction

Reading, while young in comparison to other linguistic processes like speech, plays a critical role in myriad areas of life. While some instances of reading now include reading instructions for how to play a new game on a smartphone or reading a recipe to create a new dish, it also has significant historical importance. From Korean King Yeonsangun banning the use of the logical and easy-to-learn Hangeul after being mocked with it in the 1500s to the historical controlling of literacy rates for enslaved populations to ensure forced ignorance and lessen chances of rebellion, reading has long been viewed as a tool for the masses and a weapon for tyrannical leaders. As its historical importance has been well-documented and discussed, it is thus sensible that psycholinguistics researchers have not overlooked the importance of reading and word recognition.

Indeed, many models have been put forward to explain the process by which people get from orthographic symbols to semantic and phonological information. One of the earliest models is Morton's (1969) logogen model. In this, logogens refer to units that assist in the word recognition process by storing information about words, such as their semantic or orthographic information. Thus, logogens do not store words themselves; instead, they store elements of words. Once a logogen is activated with either bottom-up perceptual input or top-down contextual input, recognition is achieved when a threshold specific to that logogen (and dependent on factors like word frequency) is reached, thereby granting access to the word's stored information. The need for activation in Morton's model led to its being categorized as an activation model.

In contrast to activation models are search models, of which Forster's (1976) is one of the most well-known. In his model, all words are stored together by frequency and each entry has orthographic, semantic, and phonological information associated with it. When perceptual information is received, the search for a matching stored word begins. The system searches through all entries that are close matches with in the input (e.g., *doom* and *door* would be close together because they share three of four letters, similar to how they would be organized in a

dictionary). Once a stored word is found, there is a verification process that ensures that the stored word indeed matches the word that initiated the search. If this is verified, the search is deemed successful and results in recognition; however, if it is not verified, then the search begins again and is more thorough in its efforts to locate the matching stored word.

Following these influential early models of word recognition, two of the most influential and modern models are the dual-route cascaded (DRC) model and the parallel distributed processing (PDP) model. The DRC (Coltheart, Rastle, Perry, Kangdon, & Ziegler, 2001) is a modular account of word recognition and, as its name implies, contains two routes that can be taken to get to the goal of recognition. The first, the lexical route, holds orthographic, phonological, and semantic information for all words in a person's lexicon, while the second, the sublexical route, translates graphemes to phonological information through a series of rules that map phonological information onto graphemes. An argument for why two routes are necessary is to account for irregular words and nonwords. For example, the sublexical route's grapheme-to-phoneme system could not correctly handle an irregular word like *yacht*, so the lexical route would need to be used to arrive at the proper pronunciation. Conversely, the lexical route could not correctly handle a pronounceable nonword like *drude* because it would not be represented in the lexicon, so the graphemes would have to be translated to phonemes by the sublexical route to arrive at the correct pronunciation.

Next, there is the PDP model of reading (Seidenberg & McClelland, 1989; see also Plaut, Seidenberg, McClelland, & Patterson, 1996), which challenges the idea that two separate mechanisms are necessary. In this connectionist model, sets of units are associated with information about words (e.g., semantic, orthographic, phonological), and these sets organize themselves into stable and consistent patterns. Between these sets are hidden units, which mediate the associations. So, for instance, when perceptual information is received, the orthographic units activate, and this activation spreads through the other units, resulting in a specific pattern of activation that is unique to a word. This pattern of activation results in recognition of the word for which the pattern is associated. This is, of course, different from many other models that place great importance on the lexicon, as PDP models assume that word representations are stored as activity patterns, while long-term storage of individual words is coded as connections among these units.

The preceding models are all quite extensive and have at least some empirical backing and theoretical supporters, but this does not stop researchers from trying to perfect models of word recognition. One recent and popular attempt to perfect these models is connectionist dual process + model (CDP+; Perry, Ziegler, & Zorzi, 2007). The CDP+ is a hybrid model that builds upon its previous iteration, the CDP (Zorzi, Houghton, & Butterworth, 1998), while also incorporating elements of the modular DRC and the connectionist PDP (among other models). For example, the CDP+ retains the necessity for separate lexical and sublexical paths in the style of the DRC, but is able to learn common and reliable grapheme-to-phoneme rules by using a network, which is more like the style of the PDP.

According to the CDP+, when a string of letters is encountered, this activates feature detectors, which determine how many characters are in the string. These feature detectors work with the letter nodes to map features to letters. Then, for real words, these letters start activating words according to the orthographic lexicon and how much overlap there is between the letters input and words in the lexicon. These orthographic activations then cause activation in the phonological lexicon. As semantic information overlaps the orthographic and phonological lexicons, word meanings are stored here. These phonological activations are then passed to the phonological output buffer, which will activate or inhibit phonemes before speech is produced. Importantly, there is feedback at every stage in the process for words.

For nonwords, on the other hand, after letter nodes have been activated, they spread to corresponding graphemes, which the system then maps to phonemes based on correspondence rules that have been learned and are deemed to be dependable. This phonological output is then passed to the phonological output buffer, which functions as it does for real words. Aside from the initial feature-to-letter process, there is no feedback for nonwords.

As detailed as they are, the preceding models seem to neglect the role that word emotionality may play in the recognition process. For example, a positive word like *happiness* may be recognized differently than a negative word like *sadness*, or an exciting word like *thrill* may be recognized differently than a calming word like *relaxation*. The potential impact of emotion in reading did not go unnoticed by Rosenblatt (2004), who developed transactional theory.

While not a model of word recognition as the preceding models are, Rosenblatt's (2004) transactional theory is nevertheless a theory of reading and focuses on how readers respond to text that they have read. To this end, transactional theory argues that readers process information by choosing a stance based on what they hope to do with the information that they are reading. These stances exist on a spectrum between the anchors of *efferent* and *aesthetic*. The efferent stance is largely oriented towards knowledge and retaining information, while the aesthetic stance allows readers to immerse themselves in the experiences of what is being read (for instance, allowing the reader to feel the emotion that the author is conveying).

When discussing a unified theory of reading that accounts for various elements of the reading process (such as transforming written information to spoken information, processing and comprehending written information, and responding to written information), Sadoski and Pavio (2007) identify transactional theory's stances as fitting into dual coding theory (DCT; first described in Pavio, 1971). DCT posits that two distinct but cooperative processing systems exist: the logogen system, which is verbal and processes visual, auditory, and motor stimuli, and the imagen system, which is nonverbal and processes information across many modalities. As information is received and sent to the respective system, verbal or nonverbal responses can be elicited. Sadoski and Pavio argue that goal states (informational or immersive) can allow text to be read and processed by the logogen system if the reader desires to derive verbal and explanatory information from the source, or by the imagen system if the reader desires to extract the imagery of the text.

Though transactional theory and its subsequent inclusion in DCT are not likely to overtake the DRC, PDP, or CDP+ in the immediate future, they nevertheless expose that words have emotional information that can affect how they are processed, and this information has largely been neglected by the dominant models. This is not to say that they are incompatible with ascribing emotional significance to words in the recognition process. Indeed, a recent review of physiological/neurological studies of visual word recognition in relation to models of word recognition found that interactive accounts hold an advantage as they are consistent with high-order (e.g., semantics) playing a role in early orthographic processing (Carreiras, Armstrong, Perea, & Frost, 2014), which similarly appears consistent with emotional information playing a part in how words are processed.

Although other models can be compatible with emotional influences in word recognition, they are seldom studied when investigating the efficacy of a proposed model, even though they present a viable semantic influence manipulation. Similarly, orthography plays a large role in all of the preceding models, which is, of course, not a novel observation, as word recognition by definition should involve a process of converting orthographic symbols to meaningful semantic information; however, this provides another interesting avenue for experimental manipulation (e.g., by manipulating legibility). The present research seeks to explore this connection between perceptual, orthographic features and semantic features further.

1.1 Emotional Influences

First, with regard to semantic features, emotional qualities of words are among the most obvious, yet they are largely neglected in most models of word recognition. This is particularly surprising for recent models because there is a sizeable literature showing that emotional aspects of words influence the processing of words, from full passages (e.g., Ferstl, Rinck, & Yves von Cramon, 2005) to single words (e.g., Estes & Adelman, 2008b; Kousta, Vinson, & Vigliocco, 2009). Interestingly, for the emotional influences of single word recognition, literature has shown inconsistent effects, such as when these influences are inhibitory and when they are facilitative (for an example of such a theoretical debate, see Larsen, Mercer, & Balota, 2006; then Estes & Adelman, 2008a; followed by Larsen, Mercer, Balota, & Strube, 2008; and finally Estes & Adelman, 2008b).

When considering emotional aspects of words, there are two primary qualities that are analyzed: *valence* and *arousal*. *Valence* measures the positivity of a word, where high valence indicates a positive word, such as *puppy*, and low valence indicates a negative word, like *corpse*. *Arousal*, on the other hand, is a measure of a word's emotional intensity. High arousal therefore indicates an emotionally exciting word, such as *shoot*, and low arousal indicates a calming word, like *nap*. As the examples above illustrate, valence and arousal are at least partially independent dimensions. As discussed below, there is evidence that both influence word recognition processes.

Some prior research has shown that low valence words elicit slower reaction times (RTs) than high valence words. For example, Wentura, Rothermund, and Bak (2000) used an avoidance-based lexical decision task wherein subjects had to decide whether to approach (indicated by a button press) or avoid (indicated by withdrawal of a pressed finger) a presented stimulus word. The authors found that, regardless of which decision was made, responses took longer to make in response to negative stimuli than in response to positive stimuli. This monotonic effect of valence on RT was similarly found by Kuperman, Estes, Brysbaert, and Warriner (2014) for lexical decision and naming tasks, albeit only when valence was split into quintiles according to frequency. Additionally, Kuperman and colleagues found the opposite effect of arousal on RT when split into quintiles: low arousal led to faster RTs.

One theoretical explanation for this effect is automatic vigilance (Platto & John, 1991). According to this account, negative stimuli are afforded more attention than neutral stimuli, which makes the response process take longer, thereby yielding longer RTs than for neutral and positive stimuli. Automatic vigilance appeals to evolution and assumes that giving more attention to a negative stimulus has the potential to mitigate a potentially deadly outcome that is more likely to arise from it than a positive stimulus. Importantly, according to Kuperman and colleagues' (2014) discussion of automatic vigilance in relation to psycholinguistic tasks, this affects the processing of the words by increasing the amount of attention given to the words and does *not* interfere with the actual semantic representations of the words. In other words, this assumes that negative stimuli are attended to longer, which delays the onset of the word recognition process, rather than the recognition process starting at the same time and taking longer to complete because it takes longer to activate the semantic representation of a negative word than a positive word.

The automatic vigilance explanation persists today, but was hit with an important critique from Larsen and colleagues (2006). In their article, the authors reviewed a wide array of studies that purportedly supported automatic vigilance and analyzed all the words that served as stimuli in those studies. It was found that the negativity of the stimuli was confounded with length, frequency, and neighbourhood size such that the low valence stimuli tended to be longer, less frequent, and had smaller neighbourhood sizes than their high valence counterparts. While the authors concluded that the slowdown for low valence words consistent with automatic vigilance

was at least in part confounded with these lexical variables, they left open the possibility that automatic vigilance does exist in some form as they found a slowdown for a specific subset of negative words, disorder-specific words (e.g., *cramp*, *disfigure*, *infected*).

When considering these disorder-specific words further, Larsen et al. (2008) found that there was an inverted-U-shaped effect of valence on RT, such that valence was facilitative when high or low, but in between the extremes was inhibitory. This effect also had an interaction with arousal, where RT for negative words was inhibited by low arousal, but was facilitated for positive words (as the disorder-specific words were low valence and low arousal, this interaction is consistent with the slowdown that Larsen and colleagues (2006) found). This inverted-U has been found by other researchers (e.g., Kousta, Vinson, and Vigliocco, 2009, and Kuperman et al., 2014 before data were split by frequency), but the valence \times arousal effect has not replicated consistently.

How could word negativity and positivity both be facilitative in comparison to neutral words? Kousta and colleagues (2009) argue that thinking of the relationship in terms of positivity and negativity is not accurate; instead, it is more sensible to think that emotionality in general is facilitative for recognition processes. This, of course, contradicts automatic vigilance in an important way: the inverted-U account assumes that negative words speed RT similar to how RT is speeded for positive words, while automatic vigilance assumes that negativity inhibits the process and positivity facilitates the process. In other words, there is no difference between high and low valence in the inverted-U account.

In presenting this explanation, Kousta et al. (2009) also provide a rationale for why this effect exists. In their account, emotional relevance in general is facilitative for word processing, and this is possible because of a preconscious influence that makes it easier to identify perceptual features of the stimulus. Expanding on this, Fritsch and Kuchinke (2013) similarly focus on perceptual features of words, but argue that these features are associated with and conditioned to the underlying emotional information, and activation of these associations occurs early in the word recognition process, thereby facilitating recognition. While Fritsch and Kuchinke do not make specific predictions about the influence of valence and arousal on RT, the facilitative

effects for emotional associations with perceptual features indicates that emotional words in general would lead to speeded RT, much like Kousta and colleagues' inverted-U.

1.2 Perceptual and Orthographic Influences

Orthography not only plays a large role in the word recognition models discussed earlier, it also plays a sizeable role in Kousta et al.'s (2009) and Fritsch and Kuchinke's (2013) accounts of emotional word recognition, though the literature exploring these connections is still fairly limited. One way to extend this research is to consider the perceptual fluency paradigm. This paradigm has been examined in many different domains, but it has yet to be used with emotional word recognition. Thus, it provides an interesting and novel way to incorporate perceptual manipulations into emotional word recognition.

Fluency, which is broad enough to encompass perceptual fluency, is defined as the level of effort required for a task. This is consistent with Alter and Oppenheimer's (2009) definition of fluency, whereby they also express that the level of effort required exists on a continuum with anchors at *highly effortless* and *highly effortful*. Generally, fluency (also referred to as *processing fluency*) is investigated in the context of metacognition, judgement, and decision-making; however, the scope of fluency research is quite wide (for reviews, see Alter, 2013 and Alter & Oppenheimer, 2009b).

While disfluency – experienced when a task is closer to the *highly effortful* anchor – has been applied in many ways and results have been shown to be quite robust (Alter & Oppenheimer, 2009b), one specific area of this research is directly applicable to the interest in exploring the roles of perceptual orthographic features in emotional word recognition: perceptual fluency. A decidedly common way to induce perceptual disfluency is to manipulate font legibility and make a fluent condition with an easily legible font and a disfluent condition with a hard-to-read font.

When perceptual disfluency is induced, people have expressed greater resistance to disclosing embarrassing personal information online (Alter & Oppenheimer, 2009a), less confidence in their judgements (Simmons & Nelson, 2006), less susceptibility to giving intuitively-biased responses to misleading questions (Alter, Oppenheimer, Epley, & Eyre, 2007;

Song & Schwarz, 2008), and less reliance on the representativeness heuristic (Alter et al., 2007). A proposed explanation for the way in which disfluency results these effects is by engaging a deeper level of processing. This tends to be couched in terms of System 1/System 2 processing, wherein System 1 is intuitive, quick, relies on emotions, and System 2 is deliberate, slower, rational. When disfluency is encountered, processing slows down, which engages System 2 and brings forth all its deliberative, rational elements. This, then, allows subjects to see past misleading questions like “How many animals of each kind did Moses bring on the Ark?” (Erickson & Mattson, 1981) and respond correctly with “none” (Song & Schwarz, 2008).

Another potential way that disfluency works is that it suppresses associations between stimulus features and their representations. This would be particularly relevant as an explanation for Alter and colleagues’ (2007) Experiment 3 finding that disfluency resulted in a diminished dependence on the representativeness heuristic. In this, subjects were given the classic account of Tom W., a fictional student who matched the stereotype of an engineering student, from Kahneman and Tversky (1973). A first group of subjects rated how similar Tom W. was to a typical student in one of nine listed subjects (of which engineering was one), while another group were split into fluent and disfluent conditions and read the description of Tom W., followed by giving a rating of how likely it was that Tom studied each of the listed majors. The second group’s ratings were then correlated with the first group’s representativeness ratings, giving a measure of the degree to which the representativeness heuristic was relied upon. Consistent with other fluency research, the ratings from subjects in the disfluent condition lined up with the representativeness scores to a significantly smaller degree than the ratings from the subjects in the fluent condition.

From its inception in Tversky and Kahneman (1973), associations between stimulus features and salient information have been at the core of the representativeness heuristic. Indeed, the authors claim “When judging the probability of an event by representativeness, one compares the essential features of the event to those of the structure from which it originates” (p. 208). Thus, it is possible that the presence of disfluency actually dampened associations between Tom W.’s features and the subjects’ mental representations of what exemplars of a certain field are typically like, and these dampened associations resulted in less reliance on the representativeness heuristic.

1.3 Present Research¹

The associations between stimulus features and mental representations are present in theories of emotional word recognition (Kousta et al., 2009; Fritsch & Kuchinke, 2013) as well as in an experiment that investigated fluency and the representativeness heuristic (Alter et al., 2007). While research explored these in separate domains, experimental interest has not yet converged to explore the effect of fluency on emotion word recognition. The present research seeks to bridge this gap by examining how a perceptual manipulation like font fluency can impact the semantic representations of single words in a naming task (which is one example of a single word recognition task).

This research does not seek to test the assumptions of a specific model of word recognition, but due to the inclusion and importance of orthography and semantics in the reviewed models, results should be applicable to any model that includes orthographic and semantic elements. The present research relies upon assumptions for emotional word recognition from Kousta and colleagues' (2009) as well as Fritsch and Kuchinke's (2013), such as the assumption that words' semantic (e.g., emotional) representations are conditioned to their perceptual features. This means that, by changing the perceptual features of a word, the semantic representation of the word should weaken. While this assumption is retained, this study does not rely upon the assumption from these models that emotionality, positive or negative, will be facilitative for RT; instead, it assumes a more linear shape in this relationship, à la Kuperman and colleagues (2014). Finally, there is reliance upon the suppressed use of the representativeness heuristic for the disfluent condition in Alter et al. (2007), which is treated as a dampening of the association between stimulus features and mental representations by the present research.

¹ This study's hypotheses were pre-registered on the Open Science Framework (OSF). All stimuli, data, and analyses are also uploaded to the OSF. These can be found at: osf.io/w5hu7

With these assumptions in mind, we hypothesize the following results:

- (1) Regardless of valence and arousal values for words, disfluent font will result in slower RTs for the naming task. This is consistent with prior fluency work, which has shown slower processing in the presence of disfluency (see Alter, 2009);
- (2) Fluency and valence will interact such that valence effects on RT are attenuated for disfluent items but not for fluent items. This is consistent with prior perceptual disfluency work that has shown that disfluency dampens associations between stimuli and stored information about those stimuli (Alter et al., 2007, Experiment 3). While disfluency research has largely been examined with passages and context-dependent tasks, the fluency effect has also been shown to be robust (Alter & Oppenheimer, 2009b) and should therefore extend to context-independent single words by diminishing associations between the words and their stored semantic information, which would in turn mitigate their influences on RT;
- (3) Fluency and arousal will interact such that valence effects on RT are attenuated for disfluent items but not for fluent items. The rationale for this hypothesis is the same for hypothesis 2.

Chapter 2

2 Methods

2.1 Subjects

Sixty-four students at Western University were recruited through Western's Psychology Research Participation Pool. To be eligible for inclusion, subjects must have been at least 18 years old, native English speakers, and had normal or corrected-to-normal vision. One subject indicated that they were a native Mandarin speaker and their data were consequently removed from consideration. Additionally, due to high error rates (greater than 20% of trials), three other subjects' data were removed consideration.

The final analysis consisted of 60 subjects (37 females) whose ages ranged from 18–21 years old ($M = 18.50$, $SD = 0.81$). Informed written consent was obtained from all subjects before participation began and all subjects were compensated with two research credits, indicating two hours of participation (the present study took approximately 30 minutes, while the remaining 90 minutes were spent on two other studies unrelated to this project).

2.2 Stimuli

We utilized a corpus containing affective norm data for nearly 14,000 English items (Warriner, Kuperman, & Brysbaert, 2013) with frequency norms for these items imported from the SUBTLEX_{US} corpus (Brysbaert & New, 2009). Warriner and colleagues used Amazon's Mechanical Turk to collect norm data from self-reported residents of the United States. They compiled 43 lists with approximately 350 words each (40 of which were control) and had 20 subjects per list rate each word on one dimension (valence, arousal, or dominance) with a 9-point scale. Subjects could choose to participate multiple times, though they could not rate the same list twice.

Three hundred and fifty English words were randomly sampled using a sampling command in R 3.3.1 (R Core Team, 2016). Sampling was not done with the goal of having items

balanced across all bins of valence and arousal; rather, we sought to have a sample that had characteristics reminiscent of the corpus (see Figure 1).

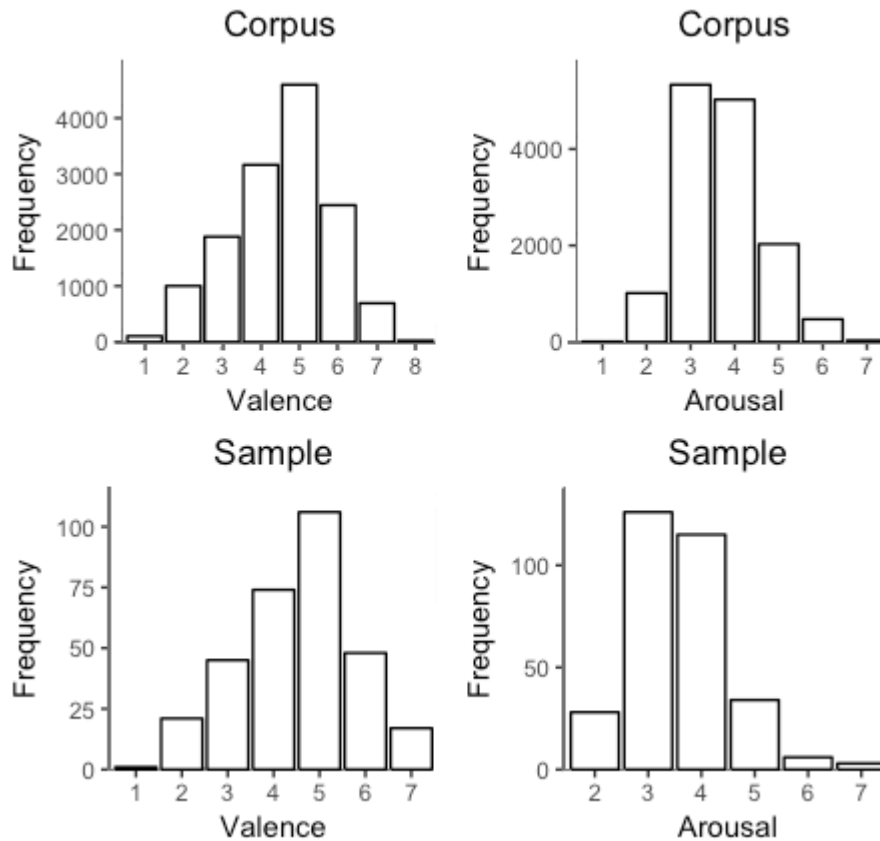


Figure 1. Histograms of valence and arousal values across the corpus and across the sample.

The stimulus items' lengths were limited to a maximum of 10 characters ($M = 6.85$, $SD = 1.84$) and were controlled for polysemy by the experimenter through a process of inspection of the sampled words and removal of those that had multiple meanings. Once these criteria were applied, the resulting list contained 325 items. From this, 10 items were randomly selected to serve as the practice list to familiarize subjects with the experimental process (see Appendix A), while the other 315 items were selected to serve as the experimental items (see Appendix B).

As fluency was a main variable in the present research, 158 of the 315 items were randomly selected to be presented in the fluent font, 28-point Helvetica (see Figure 2, top left), while the remaining 157 items were presented in the disfluent font, 24-point italicized Haettenschweiler (see Figure 1, middle), a font that has been used for the disfluent condition in

other research (Diemand-Yauman, Oppenheimer, & Vaughan, 2010). Five independent raters recruited from the Brain and Mind Institute at Western University were given these fonts, in addition to a control font that was not used in the experiment, and asked to rate them for their legibility. All of the raters scored the fluent font as the most legible while the disfluent font was scored as the least legible. A second list was generated to counterbalance the font of the items (i.e., the 158 fluent items in list one became disfluent for list two).

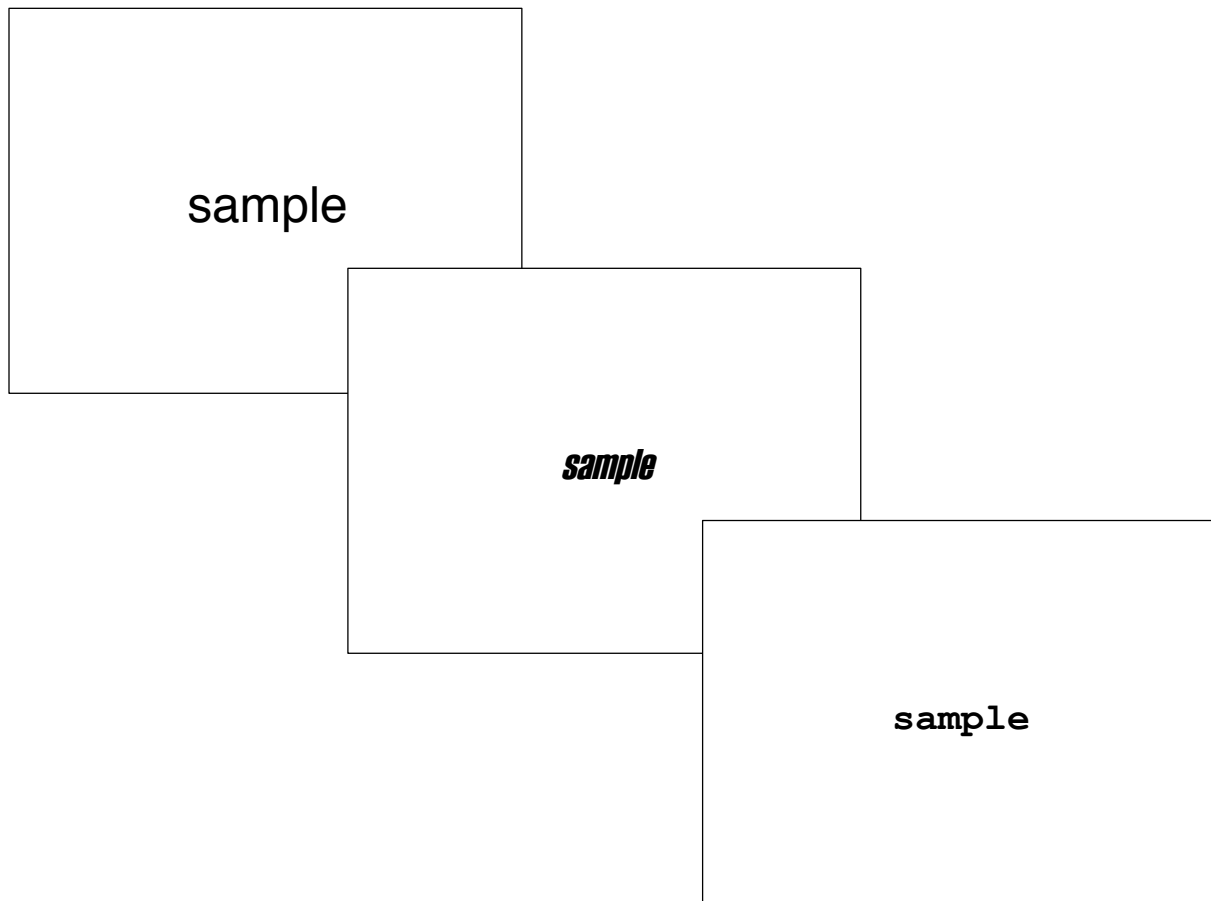


Figure 2. Fonts used in the experiment. 28-point Helvetica represented the fluent font, 24-point italicized Haettenschweiler represented the disfluent font, and 18-point bolded Courier New represented the practice font.

After data collection had begun, the experimenter noticed a few items were missed during the pruning process: *surf*, *ligature*, and *cordon*. *Surf*, while meeting the length requirement and not being polysemous, was included on both the practice list and the experimental list, while

ligature was deemed to be polysemous for its uses in linguistics and music. Finally, *cordon* was considered polysemous due to its existence in French (where it is pronounced /kɔʁdɔ̃/), a language with which many subjects were familiar due to being educated in Canada. These items were consequently removed from analyses, leaving 312 items on the experimental list (of which 157 were fluent).

Pearson's correlation was computed to ensure that valence and arousal were orthogonal, which was confirmed at the corpus-wide level, $r(13,910) = .001$, $p = .916$, as well as the sample-wide level, $r(310) = .007$, $p = .904$. Additionally, t -tests were computed to confirm that valence, arousal, and log10 frequency norms for words in the fluent condition did not significantly differ from those of the disfluent words. Following Delacre, Lakens, and Leys (2017), Welch's t -tests were used for these comparisons. Indeed, the items in each condition did not significantly differ in any of the norms (see Table 1).

Table 1. Valence, arousal, and log10 frequency comparisons between fluent and disfluent conditions.

Norm comparisons between font conditions

Norm	Mean (SD)		t (df)	p
	Fluent	Disfluent		
Valence	5.09 (1.24)	5.03 (1.28)	0.39 (309.3)	.693
Arousal	4.12 (0.86)	4.14 (0.89)	-0.16 (309.2)	.870
Log10 frequency	2.11 (0.64)	2.07 (0.65)	0.49 (309.8)	.622

Note. Presented results are for the first list ($n_{\text{fluent}} = 157$, $n_{\text{disfluent}} = 155$). For the second list, fluent and disfluent means and SDs are flipped due to counterbalancing.

2.3 Procedure

The present research was part of a larger investigation of reading processes in adults. This study was designed in E-Prime 2.0, with stimulus items entered in as individual .jpg files. The experiment was presented to subjects on a laptop with a 60 Hz refresh rate. R 3.3.1, running in the RStudio 1.0.153 environment (RStudio Team, 2017), was used to randomly assign subjects

to either the list 1 condition or the list 2 condition. Thirty subjects were randomly assigned to list 1, while the remaining 30 were randomly assigned to list 2.

Subjects first completed two demographic questionnaires before starting the naming task. For the naming task, subjects were instructed to read the presented words as quickly and as accurately as they could while positioning their mouths 1-2 cm from the microphone to ensure high-quality recordings. The experiment began with 10 practice items in order to allow subjects to become acclimated to the study procedure. These practice items were presented in 18-point, bolded Courier New (see Figure 1, bottom right) in an effort to avoid any potential font priming. After these items, subjects had a break, which was followed by presentation of the 315 experimental trials. The presentation order of the 315 experimental trials was randomized per subject by E-Prime.

For practice and experimental items, each trial began with a 250 ms presentation of a fixation cross in the centre of the screen, followed by a 3000 ms presentation of the target, and concluded with a 500 ms presentation of a blank screen. The target was presented for the entire 3000 ms and did not terminate upon vocal onset. Following the conclusion of the naming task, subjects completed two other tasks beyond the scope of the present research.

To record .wav files and RTs for spoken responses on each trial, the Chronos response device was used; however, the RTs that Chronos reported showed significant variability and outlier effects due to problems with matching the microphone sensitivity to the vocal responses. Therefore, the recorded .wav files were loaded into CheckFiles, from the CheckVocal software (Protopapas, 2007), to aid in manually calculating RTs. Finally, two independent raters who were not authors of this study were recruited to score responses for accuracy. The researcher scored all trials for which there was a lack of concordance between the other raters.

Chapter 3

3 Results

Before inspecting the data for outliers, RT data from the three items eliminated from the sample stimuli (*surf*, *ligature*, and *cordon*) were removed, reducing the dataset from 18,900 observations to 18,720. Following this, all trials on which subjects made an error, gave no response, or for which RT could not be ascertained due to microphone interference, inaudible response, etc. were removed. This reduced the dataset to 17,250 observations. Subjects made an average of 24.42 errors ($SD = 9.65$) for 312 trials, representing an error rate of 8%.

To correct for skewness that is typical of RT data (skewness = 2.24; see the top of Figure 3), a median-based outlier detection and removal process was used. Outliers are traditionally detected and removed through a method related to the data's SD, followed by a logarithmic transformation; however, the present research followed Leys, Ley, Klein, Bernard, and Licata (2013) and utilized median absolute deviation (MAD) to do this. Leys and colleagues argue that, because there are undoubtedly outliers in the sample, using the mean and SD allows these outliers to exert considerable influence over the detection of other outliers.

The MAD is computed from the median of the distribution (in this case, 688 ms). A specified deviation threshold is then multiplied by the MAD and is then added to (for the upper limit) and subtracted from (for the lower limit) the distribution's median. As recommended by Leys and colleagues (2013), 2.5 times the MAD was used as the threshold for outlier detection. Thus, the upper limit for detection was 1,058.65 ms while the lower limit was 317.35 ms. Using this method, 1,408 observations were removed, yielding 15,842 observations in the final dataset (of which 8,312 were for fluent items). As apparent in Figure 3 (bottom), the dataset approximated a Gaussian distribution (skewness = 0.50) after removing inaccurate trials and outliers for the complete dataset as well as when split by font condition.

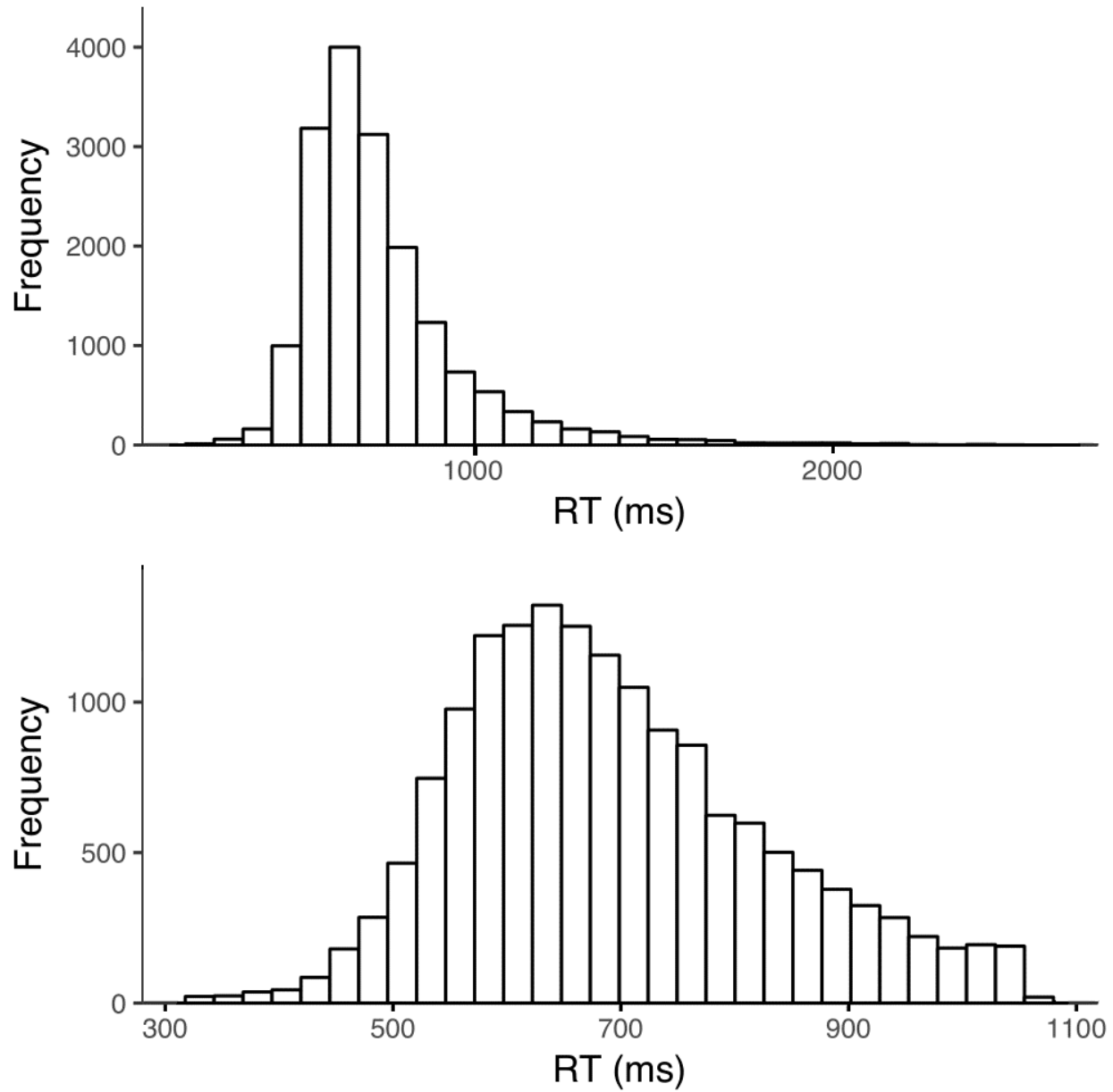


Figure 3. Histograms before (top) and after (bottom) outliers were removed using MAD.

3.1 Model Selection

A linear mixed-effects model, run with the R package *lme4* (Bates, Maechler, Bolker, & Walker, 2015), was used to examine the effect that each variable exerted on RT, and to specifically test the hypothesis that a disfluent font would modulate the effects from valence and arousal on RT. Linear mixed models, which are a form of regression, afford the ability to use both within- and

between-subjects constructs while also controlling for variance from random sampling (e.g., subjects and items for the present research), and are also quite robust to random missing data (Gueorguieva & Krystal, 2004). These factors contributed to the decision to use a mixed model in lieu of the more traditional analysis with an ANOVA. Restricted maximum likelihood estimation (REML) was used to fit models when appropriate (Oehlert, 2012), and the *lmerTest* package for R (Kuznetsova, Brockhoff, & Christensen, 2017) was used to compute *p*-values based on Welch-Satterthwaite estimates of the degrees of freedom.

In the model, intercepts for subjects and items were entered as random effects. To determine which other factors significantly contributed to the prediction of RT, each one was entered as a fixed effect into a base model containing only the dependent variable (RT) and the two random effects. This process revealed that font, valence, item length, and trial number were all significant predictors of RT when the random effects were accounted for and were thus included as fixed effects (see Table 2). While arousal was not a significant predictor on its own, it was nevertheless included in the model due to its relevance to the hypotheses.

Table 2. Statistics for how well each variable predicted RT.

<i>Variable statistics</i>					
Variable	β	<i>SE</i>	<i>t</i>	df (estimate)	<i>p</i>
Fluent font	-58.39	1.64	-35.52	15,474.4	< .001
Valence	-9.79	2.55	-3.84	300.6	< .001
Arousal	-3.34	3.75	-0.89	301.4	.374
Log10 frequency	8.41	5.09	-1.65	300.6	.099
SUBTLEX _{US} frequency	-0.01	0.06	-0.09	296.3	.928
Length	10.29	1.69	6.10	299.5	< .001
Trial	0.03	0.01	3.57	15,503.4	< .001

Note. All variables were fitted as fixed effects in the formula $RT \sim [variable] + (1 | subject) + (1 | item)$ and were fitted with REML. β s are based on their relation to the intercept (in this case, disfluent font). Thus, positive values indicate an increase in RT for disfluent items, while negative values indicate a decrease in RT for disfluent items.

To select the model with the most explanatory power, valence and arousal were first split and examined separately. For valence, three models were chosen: (1) a model with valence and all the other fixed and random effects, but without font; (2) another with font, valence, and the other fixed and random effects; and (3) one with an interaction of font and valence, along with the other fixed and random effects. The fits of models 2 and 3 were very close, as measured by AIC (192,880 and 192,879, respectively), so they were compared via a χ^2 test using the *car* package for R (Fox & Weisberg, 2011). This revealed that models 2 and 3 did not differ significantly in how well they fit the data, $\chi^2(1) = 2.77, p = .096$. While the simpler model (without the interaction term) would generally be used going forward, the font \times valence effect was retained. This decision was made due to its not being significantly worse at fitting the data than the simpler model, coupled with the experimental interest in seeing if the interaction

changed when arousal was eventually included in a complete model. Model 3 (see Table 2) was then compared to model 1, which had the worst fit for the data as measured by AIC (194,088), and fit the data significantly better, $\chi^2(2) = 1,213.00, p < .001$, resulting in retention of model 3's interaction term when fitting the complete model.

Table 3. Statistics for the fixed effects in model 3.

<i>Model 3 statistics</i>					
AIC	BIC				
192,879	192,949				
Fixed Effect	β	SE	<i>t</i>	df (estimate)	<i>p</i>
(Intercept)	715.27	20.08	35.62	381.6	< .001
Fluent font	-69.35	6.82	-10.17	15,512.7	< .001
Valence	-11.02	2.56	-4.30	349.0	< .001
Length	10.27	1.69	6.07	301.6	< .001
Trial	0.03	0.01	3.58	15,496.9	< .001
Fluent \times Valence	2.15	1.29	1.66	15,507.2	.096

Note. This model was fitted with the formula $RT \sim (\text{font} * \text{valence}) + \text{length} + \text{trial} + (1 | \text{subject}) + (1 | \text{item}), \text{REML} = \text{FALSE}$. β s are based on their relation to the intercept (in this case, disfluent font). Interaction β s are based on the fixed effect β for the disfluent condition (in this case, the β for Fluent \times Valence indicates $-11.02 + 2.15$, or -8.87).

Next, for arousal, three models were chosen in the same way that they were for valence: (4) one with arousal and all other fixed and random effects, but not including font; (5) one with font, arousal, and the other fixed and random effects; and (6) one with an interaction of font and arousal, along with the other fixed and random effects. According to AIC, models 5 and 6 fit the data best (192,895 and 192,886, respectively), so they were compared. The χ^2 test revealed that model 6 (see Table 4) fit the data significantly better than model 5 did, $\chi^2(1) = 10.53, p = .001$,

leading to retention of the interaction term when fitting the complete model, as was the case with valence.

Table 4. Statistics for the fixed effects in model 6.

<i>Model 6 statistics</i>					
	AIC	BIC			
	192,886	192,955			
Fixed Effect	β	<i>SE</i>	<i>t</i>	df (estimate)	<i>p</i>
(Intercept)	688.91	21.59	31.91	392.5	< .001
Fluent font	-83.79	8.02	-10.45	15,491.9	< .001
Arousal	-7.48	3.78	-1.98	351.2	.049
Length	10.38	1.73	6.05	301.2	< .001
Trial	0.03	0.01	3.53	15,495.5	< .001
Fluent \times Arousal	6.14	1.89	3.25	15,493.7	.001

Note. This model was fitted with the formula $RT \sim (\text{font} * \text{arousal}) + \text{length} + \text{trial} + (1 | \text{subject}) + (1 | \text{item})$, $REML = \text{FALSE}$. β s are based on their relation to the intercept (in this case, disfluent font). Interaction β s are based on the fixed effect β for the disfluent condition.

Finally, with the results from the prior comparisons in mind, a final model was generated by including the font \times valence term and the font \times arousal term. The resulting model, model 7 (see Table 5), fit the data better than models 3 and 6 according to AIC (192,872 compared to 192,879 and 192,886, respectively). Accordingly, comparing model 7 with model 3, the model with the next best fit, showed a significantly better fit for the data, $\chi^2(2) = 11.55, p = .003$.

Table 5. Statistics for the fixed effects in model 7.

Model 7 statistics

	AIC	BIC			
	192,872	192,956			
Fixed Effect	β	<i>SE</i>	<i>t</i>	df (estimate)	<i>p</i>
(Intercept)	744.54	24.87	29.93	398.9	< .001
Fluent font	-94.91	10.28	-9.14	15,477.2	< .001
Valence	-10.94	2.56	-4.28	349.4	< .001
Arousal	-7.30	3.70	-1.97	354.4	.049
Length	10.35	1.69	6.12	301.6	< .001
Trial	0.03	0.01	3.54	15,494.4	< .001
Fluent \times Valence	2.06	1.29	1.59	15,482.0	.112
Fluent \times Arousal	6.07	1.89	3.20	15,493.0	.001

Note. This model was fitted with the formula $RT \sim (\text{font} * \text{valence}) + (\text{font} * \text{arousal}) + \text{length} + \text{trial} + (1 | \text{subject}) + (1 | \text{item})$, REML = FALSE. β s are based on their relation to the intercept (in this case, disfluent font). Interaction β s are based on the fixed effect β for the disfluent condition.

Throughout all models, font fluency was associated with a significant decrease in RT. This difference was also apparent in the average RT for fluent items ($M = 668.83$, $SD = 130.36$) being markedly quicker than RT for disfluent items ($M = 720.89$, $SD = 136.56$). These results, coupled with the font legibility ranking data, provide support for the expectation that disfluency would result in longer processing times thus increasing RT.

The results from model 7 do not provide support for the hypothesis that disfluency would lead to attenuated influences of valence and arousal. For both fluent and disfluent fonts, increasing valence led to faster RT, which is in line with past results (e.g., Kuperman, Estes,

Brysbaert, & Warriner, 2014). Interestingly, though, the present results suggest that arousal is modestly facilitative for items presented in the fluent font ($\beta = -1.23$; see Figure 4, top) and significantly more facilitative for items in the disfluent font ($\beta = -7.30$; see Figure 4, bottom). The facilitative effect of arousal deviates from the results in Kuperman and colleagues' work as well as the present hypotheses; however, this effect is not unprecedented (e.g., Larsen et al., 2008).

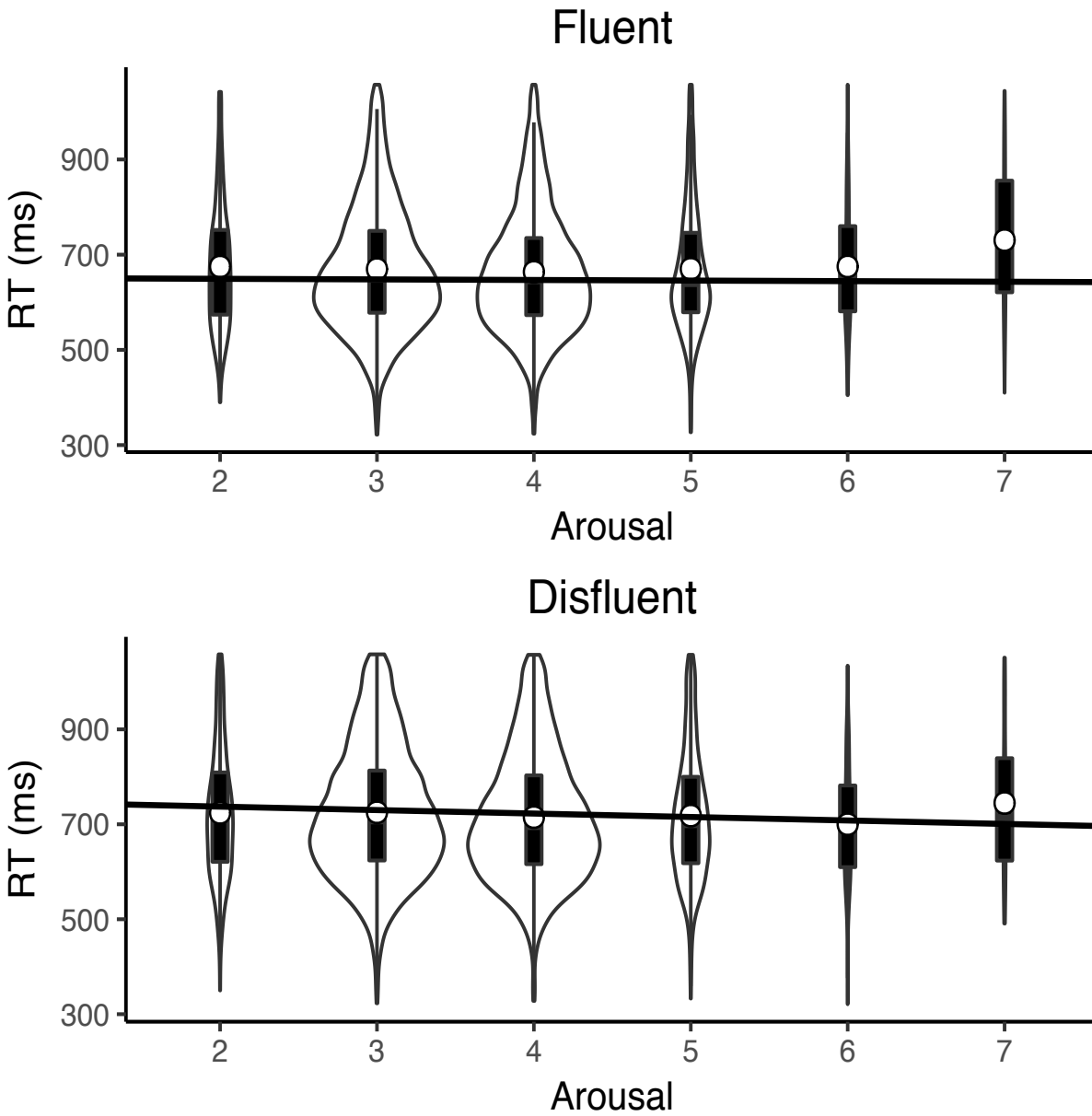


Figure 4. Violin plots showing fit lines across binned arousal values. Circles indicate means, width indicates density, and boxes represent data from the 25th to 75th percentile.

3.2 Exploratory Analyses

In addition to the preceding analyses, which served to test our preregistered hypotheses, we ran exploratory analyses to test hypotheses that were developed after data collection had begun. As some researchers have found valence \times arousal interactions (e.g., Larsen et al., 2008),

we first wanted to see if we could replicate this effect. The valence \times arousal interaction term was first put into a base model containing only RT and the two random effects, $RT \sim (\text{valence} * \text{arousal}) + (1 | \text{subject}) + (1 | \text{item})$. This revealed that there was not a significant interaction between valence and arousal, $t(299.81) = -0.92, p = .359$.

Though the interaction was non-significant in the base model, we still wanted to ensure that it was not manifesting in the complete model, so we included the interaction term in model 7, which was deemed our best fitting model. The resulting model, model 8 (see Table 6), did not fit the data better than model 7 according to AIC (192,874 compared to 192,872, respectively). Using a χ^2 test, we did not find that there was a significant difference in fit between models 7 and 8, $\chi^2(1) = 0.22, p = .640$. Due to the non-significance of the interaction term and the slightly better fit of model 7 according to AIC, we failed to replicate the valence \times arousal interaction, much like Kuperman and colleagues (2014) did.

Table 6. Statistics for the fixed effects in model 8.

Model 8 statistics

	AIC	BIC				
	192,874	192,966				
Fixed Effect	β	<i>SE</i>	<i>t</i>	df (estimate)	<i>p</i>	
(Intercept)	717.71	65.55	11.47	322.4	< .001	
Fluent font	-93.99	10.28	-9.14	15,492.2	< .001	
Valence	-5.60	11.69	-0.48	304.8	.632	
Arousal	-0.95	14.07	-0.07	308.2	.946	
Length	10.28	1.70	6.06	301.7	< .001	
Trial	0.03	0.01	3.54	15,509.3	< .001	
Fluent \times Valence	2.06	1.29	1.59	15,497.2	.111	
Fluent \times Arousal	6.06	1.89	3.20	15,506.7	.001	
Valence \times Arousal	-1.24	2.65	-0.47	302.7	.641	

Note. This model was fitted with the formula $RT \sim (\text{font} * \text{valence}) + (\text{font} * \text{arousal}) + (\text{valence} * \text{arousal}) + \text{length} + \text{trial} + (1 | \text{subject}) + (1 | \text{item})$, $REML = \text{FALSE}$. β s are based on their relation to the intercept (in this case, disfluent font). Interaction β s are based on the fixed effect β for the disfluent condition.

Chapter 4

4 Discussion

The goal of the present research was to examine the interaction of perceptual fluency and emotional qualities of words. This was explored by using words' valence and arousal norms as measures of their emotionality, perceptual fluency manipulations, and testing RTs with a naming task. While the broad expectation was that perceptual disfluency would mediate emotional influences on RT, this was not found to be the case, as disfluency, when interacting with valence and arousal, was more facilitative than fluency.

Specifically, hypothesis 1 anticipated that items presented in the disfluent font would yield slower RTs than items presented in the fluent font. This was supported by the data, as the RT for disfluent items was significantly slower than for fluent items, by approximately 50 ms. Hypothesis 2 expected attenuated influence of valence on disfluent items compared to fluent items. This was not supported, as RTs became faster with increasing valence in both conditions, rather than for the fluent condition alone, as predicted. While not statistically significant, valence was more facilitative for disfluent items than fluent items. Finally, hypothesis 3 postulated attenuated influence of arousal on disfluent items compared to fluent items. This was also not supported, as RTs became faster with increasing arousal in both cases, and this effect was significantly stronger for disfluent items than fluent items.

Many models of word recognition presently do not reserve a role for words' emotional qualities, though these have been consistently shown to play a part in word recognition (e.g., Kuperman et al., 2014; Larsen et al., 2008); however, interactive models do seem to provide the easiest path for studying the role of emotion in word recognition. A model that aims to predict the effects emotional information has on recognition RT would have the ability to provide feedback between orthography and semantics, as this could explain how certain pieces of semantic information, such as emotional content, can activate early and influence the rest of the process, thereby influencing RT.

While this study did not seek to test any models specifically, the present results nevertheless further underscore the importance of including those emotional features in word

recognition models as, even after implementing lexical and sublexical controls, valence and arousal were still found to play a significant role in RT. While dominant models are able to explain many phenomena, there is still much work to be done in developing a model that can predict effects with extraordinary ability (Adelman, Marquis, Sabatos-DeVito, & Estes, 2013). Such an endeavour would undoubtedly have to explain emotional effects on word recognition RT, and may also require a mechanism by which perceptual manipulations can impact the recognition process.

In considering how and where disfluency might manifest and exert influence in a model of word recognition, it is sensible to believe that it would occur at the initial stages. As disfluent visual input is harder to digest, this seems to delay the onset of the recognition process, evidenced by slower RTs in the disfluent condition. Two possibilities immediately become apparent: (1) a delay in the recognition process induced by disfluency could simply delay the onset of the otherwise normal process; or (2) a delay in the recognition process is due to the system accommodating disfluent visual input by adapting its mechanisms. The interaction between arousal and disfluency perhaps provides a mechanism by which partial orthographic input is put to a semantic network, and these two systems provide feedback such that the semantic representation of a disfluent word plays a larger role in recognition than it would for a fluent word. In this case, the system might opt not to rely heavily on the entirety of the disfluent visual input. While these possibilities are entirely speculative, if effects like the present results are found consistently, further research would be needed to resolve the role of disfluent input into a word recognition model.

4.1 Emotional Word Recognition

As word recognition models do not account for emotional effects from words, the natural extension of this study's implications is for models of emotional word recognition. Much like with word recognition, this study did not test specific models of emotional word recognition; however, the results can nevertheless support parts of certain models, as well as shed light on shortcomings and identify other mechanisms that may need to be included in future models.

While Fritsch and Kuchinke's (2013) model seems to be a natural fit due to its emphasis on perceptual features of emotional words and the present research's use of perceptual fluency as a manipulation, there are indeed some inconsistencies between these findings and the predictions of the model. Their feature-based model assumes that perceptual elements of words are associated with the emotional qualities of the words, and this association, when activated by attempting to recognize a word, facilitates the recognition process. Thus, emotional qualities, whether positive or negative, would be facilitative, yielding an inverted-U shape. This is similar to Kousta and colleagues' (2009) and Larsen and colleagues' (2008) inverted-U predictions. However, while the present results show facilitative effects for valence and arousal, they are monotonic effects. As valence increases, so too does its facilitative effect, and the same is true for arousal. These are contradictory for the inverted-U shape account, which does not predict a linear shape.

Automatic vigilance (Platto & John, 1991) predicts a linear effect, albeit for valence only. Because negative stimuli are afforded more attention due to their potential danger, RTs for low valence items are expected to be slower than for high valence items. This was indeed the case with the present study, as it was in Kuperman and colleagues' (2014) results that found support for automatic vigilance. This still leaves the issue of arousal, which does not have a role in the automatic vigilance framework.

It does seem sensible that high arousal words, those that are emotionally exciting, would prompt faster action, thus faster RTs. Indeed, this facilitative effect for high arousal is not unheard of, though it tends to be accompanied by a valence \times arousal interaction that was not found here (for example, Kuperman et al. (2014) found monotonic effects of arousal without an interaction with valence, but they found arousal to be inhibitory at high levels). As well, the direction of the valence \times arousal interaction is typically found in the form of a facilitative effect of arousal for low valence items (e.g., Hofmann, Kuchinke, Tamm, Vö, & Jacobs, 2009; Larsen et al., 2008), though Truong and Yang (2014) found a facilitative effect of arousal for high valence items.

One framework that can help account for this effect is the dual competition model (DCM; Pessoa, 2009). In this, both emotion and motivation play roles in the competition between

perceptual and executive processing. While motivation is not expected to play much of a role in a naming task, the emotional side seems quite relevant for these results. According to the DCM, emotional stimuli are given prioritized attention compared to neutral stimuli; however, this is not prioritized in such a way that would lead to an inverted-U à la Larsen and colleagues (2008). Rather, high-threat, risky stimuli (low valence, high arousal) facilitate processing, while low-threat, safe stimuli (high valence, low arousal) still receive prioritized processing, but can range from modestly facilitative to inhibitory (referred to as “soft prioritization” by Pessoa).

Interestingly, processing fluency is associated with positive affect, while disfluency is associated with negative affect (Reber & Greifeneder, 2017; also see Reber, Schwarz, & Winkielman, 2004). Additionally, disfluency is associated with risk (Alter, 2008; Alter & Oppenheimer, 2008; Song & Schwarz, 2009). Thus, because disfluency is perceived as risky and instills negative affect, it is possible that the facilitative effect we found from high arousal in the disfluent condition is a result of the DCM’s prioritized processing of risky, high-threat stimuli. In other words, the font itself would have been the high-threat stimulus that received prioritized processing and led to the facilitative effect. This would also explain why arousal was significantly less facilitative, and why valence was less facilitative (though not significantly), for fluent items. Moreover, like automatic vigilance, the DCM is consistent with facilitative effects for high valence.

Contrarily, use of the DCM in the perceptual fluency paradigm would presumably yield a three-way fluency \times valence \times arousal interaction, which was not found in the present results. Similarly, the DCM would predict a low valence \times high arousal interaction that was also not found. It is also possible that these interactions do actually exist, but were not found in the present study. While we randomly sampled items from the Warriner et al. (2013) and ensured that the sample did not differ from the corpus in valence or arousal, we did not ensure that the sample was balanced such that there was equal representation of each level of valence and arousal. Having equal numbers in each bin would not necessarily increase ecological validity, as readers do not typically encounter words at either extreme at the same frequency as words in the middle, but having such a balance would be useful to ensure that the effect is not being driven almost entirely by items in between the extremes. In the present study, words at the extremes of

the valence and arousal spectra were underrepresented compared to words in the 3, 4, and 5 bins, so perhaps this made us miss an interaction that would fit neatly into the DCM framework.

It is also possible that the facilitative effect of high arousal is no fluke, as Estes and Adelman (2008b) found, but is not found consistently. One potential reason for this is that arousal, compared to valence, has a fairly weak effect on word recognition. Because Estes and Adelman tested whether or not automatic vigilance generalized across levels of arousal and did not adapt a new model to accommodate the main effect of arousal, and also assume a categorical rather than linearly-shaped effects of valence and arousal, the present results necessitate a theoretical framework that accounts for facilitative effects of both high valence and high arousal, as well as monotonic effects of the two variables. Such a model could pull from automatic vigilance and assume that positive stimuli prompt faster processing and action because they are deemed not threatening. Similarly, high arousal items could prompt faster processing and action because they are emotionally exciting, and this excitement could be the catalyst for the faster action. Importantly, this would not be for risky stimuli that are low-valence and high-arousal (e.g., *massacre*), as these might prompt more attention because of their threatening nature. Similarly, high-valence, high-arousal stimuli (e.g., *sex*) may not be significantly distinguishable from the separate facilitative effects of high valence and high arousal, hence the lack of significant valence \times arousal interaction.

4.2 Fluency

If the DCM is used to interpret the present results, then the most obvious implication from this study is added support to the claim that disfluency is perceived as risky (Song & Schwarz, 2009) and induces negative affect (Reber & Greifeneder, 2017). Because the fluent condition showed weaker facilitative effects for valence and arousal, the risk and negativity imbued by the disfluent font could have driven the effect more than the valence and arousal of the words themselves. One concern about this interpretation is that it seems to predict a significantly facilitative main effect for disfluency, which was not found. Nevertheless, it remains possible that the facilitative risk of disfluency only becomes manifest when interacting with arousal (and, to a lesser extent, valence).

An alternate interpretation that does not predict a facilitative main effect for disfluency is that something about disfluency simply amplifies the facilitative effects of valence and arousal. In such an interpretation, perhaps the processing difficulty associated with the disfluent font introduces uncertainty into the recognition process, thereby increasing reliance on other cues (e.g., semantic information) in an effort to overcome this uncertainty and deem the word to be correctly recognized. The preference for fluent cues is not unprecedented (Alter & Oppenheimer, 2009; Shah & Oppenheimer, 2007), so it may be that a person finds the disfluent font as an unreliable cue for recognition, consequently leading them to focus on a more easily processed (i.e., more fluent) cue like the semantic representation of the word they are trying to recognize and verbalize. Because of the increased reliance on semantic information, the effects from valence and arousal would be amplified in the disfluent condition, while this would not be true for the fluent condition because the perceptual features of those words are deemed to be reliable.

Indeed, other researchers have found effects of partial orthography activating semantics in such a way that a word's orthographic neighbours are activated. A classic example of this is Forster and Hecor's (2002) *turple* effect, whereby researchers asked subjects if a presented word was a type of animal. Of the nonwords given, some were one letter off from the name of an animal (e.g., *turple* for *turtle*). Nonwords like *turple* had slower RTs than nonwords that were one letter off from a non-animal real word, which indicated that *turple* had activated *turtle*, thus suggesting that partial orthography can activate semantics and in turn activate orthographic neighbours. This effect, which is not limited to English (e.g., Hino, Lupker, & Taylor, 2012), lends credence to the claim that readers could view disfluent input and have partial orthography guide them to the semantic (therefore, emotional) representation, which would strengthen the effects of emotional factors. For fluent input, this would not necessarily be the case as, absent a word that would be expected to activate semantics with partial orthography (e.g., *turple*) and absent an unreliable cue like disfluency, the recognition process would behave normally.

Additionally, while perceptual fluency has typically been couched in terms of metacognition and processing fluency at large, the present results call for speculation that it may be well-suited to the stimulus degradation domain. In the degradation literature, like perceptual fluency, subjects are typically presented with items that are printed clearly or that are harder to read; the difference, however, is that, while perceptual fluency is typically investigated with

judgement, decision-making, and metacognitive tasks and is presented as hard-to-read consistently, the degradation literature is typically employed to investigate psycholinguistic processes and stimuli are degraded over time. These differences notwithstanding, several well-documented findings from the degradation literature were found with our disfluent condition. For example, degraded stimuli tend to be responded to slower (Becker & Killion, 1977), which was indeed the case for our disfluent condition.

Perhaps more interestingly, semantic priming effects tend to be larger with degraded stimuli compared to clear stimuli (e.g., Holcomb, 1993; Whittlesea & Jacoby, 1990; Yap, Balota, & Tan, 2013). This is thought to be due to readers seeking out additional information when a stimulus is degraded in an effort to resolve the processing difficulty. Through this, priming effects are due to a heightened reliance on other cues. This is quite similar to the second interpretation of the present findings' relation to fluency: that subjects may have found perceptual elements to be unreliable cues, which caused them to rely on other cues more. Moreover, the stronger semantic priming effects of degraded stimuli would be consistent with the stronger effects of arousal and (to a lesser extent) valence with disfluency that we found. Thus, it cannot be concluded that disfluency and degradation are entirely separate constructs, despite their slight differences in duration and the domains that they have been used in.

The present results provide some evidence for an interpretation that disfluency imbues risk, which drove the facilitative effects, and an interpretation that disfluency imbues uncertainty and is perceived as an unreliable cue, which increased reliance on other, more reliable cues (e.g., semantics), and this was a catalyst for the facilitative effects; however, this conflict cannot be adequately resolved unless more research is done. Further, items were not presented in blocks of the same font; instead, the displayed font was interleaved throughout the study and varied across participants. Thus, the effects of presenting alternating trials cannot be discounted. This interleaving, coupled with the fact that words were presented for only 3000 ms at a time, makes it possible that more sustained exposure to disfluency would elicit different effects. Though we found effects that are consistent with prior fluency work, some caution is nevertheless advised when interpreting these findings.

4.3 Limitations

While the font we selected for our disfluent condition (24-point, italicised Haettenschweiler) was indeed harder to read than the font for our fluent condition (28-point Helvetica), there are a few confounds about these fonts that could have played a role in the present results. First, the fluent font was larger than the disfluent font. This is significant because, when processing emotional words, a larger font is associated with earlier onsets and longer durations of emotional effects, as measured by event-related potential (ERP; Bayer, Sommer, & Schacht, 2012). As well, the fluent font was likely more familiar to subjects than the disfluent font. Helvetica, for instance, was the main font used in the iPhone user interface from 2007 to 2010, when it was replaced with a Helvetica derivative (Helvetica Neue) that was used until 2015, and is one of the most famous fonts in use. The familiarity with the fluent font is relevant because, like font size, a familiar font elicits earlier emotional ERP effects than an unfamiliar font (Kuchinke et al., 2014).

Because using a larger or more familiar font would be expected to elicit faster RTs compared to a smaller or less familiar font, it is recommended that future research avoids using fonts that vary in size and familiarity. One potential remedy for this situation is to use the same font for either condition, and degrade the one in the disfluent condition while retaining its size. For example, the fluent font could be 12-point Times New Roman printed black, while the disfluent font could be 12-point Times New Roman printed in light grey, which would increase the difficulty of processing it. Another option is to create novel fonts that are the same size, but vary in legibility, which could be used to measure fluency effects without size and familiarity confounds. Future research could also elucidate whether or not size effects taper off past a certain size. For example, there may be onset and duration differences elicited between a 14-point font and an 8-point font that may not exist between a 48-point font and a 42-point font.

Another potential limitation is that, by switching fonts throughout the study and not using blocks of the same font, subjects had to devote additional cognitive resources to attending to the font before being able to begin the word recognition process. Even in the fluent condition, the average RT was 669 ms, which is considerably longer than average word naming RT absent any other manipulation (e.g., Allen, Bucur, Grabbe, Work, & Madden, 2011; Schilling, Rayner, & Chumbley, 1998). This additional resource allocation could have also played a role in some

counterintuitive findings, like the lack of a word frequency effect. Perhaps attending to the font and including one more factor in the recognition process was enough to mitigate facilitative effects typically found with high frequency words.

When attempting to remedy this limitation, an additional concern is that including too many disfluent items together will allow subjects to read the font more easily (i.e., more fluently), which will block disfluency effects from manifesting. One solution to this is to make short blocks wherein font stays consistent, which would allow subjects to know that font will not be at risk of changing after each item, but would also not allow them to become overly familiar with the disfluent font. Using blocks of a third font would also be useful to lessen subjects' ability to predict which font would be in the next block, and would hopefully allow the disfluency effects to become apparent.

4.4 Future Directions

A clear direction for this research to go is to help inform models of emotional word recognition. While there is debate and inconsistency among present models, these findings support the claim that perceptual features play some role in emotional word recognition. These features should be explored further and incorporated into future models' mechanisms, which can hopefully increase the models' explanatory power while giving new predictions that can be tested to further our understanding about how these words are processed.

Expanding on this, it is sensible that models of emotional word recognition should then be reconciled with general models of word recognition. While there are already detailed accounts on either side, research showing the roles that word valence and arousal play in the recognition process suggests that the two sides of recognition modelling should converge into new models that can account for the mechanisms of recognition while showing the role of emotional influences in this process. As there are still inconsistencies in emotional word recognition research, perhaps only the effects that have the most support and that are the most robust could play roles in testing general word recognition models. This would serve well to start unifying effects found in either domain.

For fluency, this study provides (to our knowledge) the first look at perceptual fluency's application to single word recognition. Given the importance of reading in the typical judgement and decision-making tasks that have been used in the perceptual fluency paradigm, this seems like a reasonable route to move in. The hope is that, by learning more about how perceptual manipulations influence context-independent single words, this would lead to more informative explanations for how these manipulations influence context-dependent decision-making tasks. Additionally, this study provides a possibility that effects typical of disfluency would be similar to effects typical of stimulus degradation. These domains are at present separate, but it is not clear that this should be the case. More work should be done to determine how much overlap exists between these two constructs.

Finally, while this study is not the first to examine fluency's role on emotion, the literature on this topic is sparse. Thus, future research should aim to investigate how fluency and disfluency impact the emotional effects of stimuli, beyond the extant findings that disfluency imbues risk and negative affect. One theoretical route to utilize for this line of research is the cognitive-experiential self-theory (CEST; Epstein, 1985; Kirkpatrick & Epstein, 1992). The CEST operates very similarly to the System 1/System 2 dual-process model, which has been used as the theoretical framework by which perceptual fluency operates (Alter et al., 2007). For example, the experiential-self is fast, intuitive, and associative, much like System 1, while the cognitive-self is slow, deliberative, and analytical, much like System 2; the difference, however, is that emotions are thought to play a much larger role in the experiential-self than they do in System 1. Because of the predictive similarities between CEST and System 1/System 2, future research could use fluency manipulations on emotional stimuli to explore which dual-processing model best fits the phenomena.

4.5 Conclusions

While we sought to use perceptual disfluency to find an attenuated role of valence and arousal on word naming, we instead found that they played a larger role when font was disfluent than when font was fluent. The facilitative effect of high valence is common, while the facilitative effect of high arousal is unexpected. Fitting these emotional effects into an existing model of emotional word recognition is difficult, as we found no model that predicts facilitative,

monotonic effects of valence and arousal; however, some models, namely the DCM, seem to fit better than others. These results also strengthen Fritsch and Kuchinke's (2013) claim that perceptual features of words seem to play a role in the recognition process, but more research is needed to yield a better understanding of this role.

For processing fluency, this study extends the paradigm to emotional word reading, a novel application of fluency research. The results support the claim that disfluent stimuli are processed more slowly than fluent stimuli and provide some support for prior findings that disfluency is associated with negative affect and is perceived as risky; however, it leaves open the possibility that disfluency, rather than providing a facilitative bonus due to its threatening nature, simply amplifies facilitative effects from valence and arousal by making subjects rely more heavily on semantic information because the perceptual information is unreliable. Further research is needed to determine which of these, if either, is the more accurate explanation.

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Appendices

Appendix A

Alphabetized practice list

ankle
invent
mirror
passion
satisfactory
sure
surf
surgical
thankful
wing

Appendix B

Alphabetized experiment list

acquire	caviar	drip	grab
adore	celibate	dubious	grandpa
adoring	chaste	eggnog	growth
affection	chitchat	ensemble	guiding
aggravate	classical	enzyme	gunplay
ale	clout	essential	halftime
alpine	cockeyed	establish	hall
angelic	complexity	evaluation	hardship
annul	condition	exchange	hatred
antelope	contribute	exclude	hazard
arty	copycat	exhume	headband
astronomy	cordial	exotic	heathen
atrocious	cordon	expect	herbs
audio	corpse	eyelash	hitter
balmy	cortisone	fairway	hobo
bandage	crave	fallback	honorable
bath	crude	fare	humidity
bathing	cynicism	farm	hygienic
bid	dad	fasten	hymen
bikini	damp	feedback	hypocrite
bilateral	debriefing	feller	illness
birdcage	deceit	fertilize	immaterial
blaster	definite	fetish	impair
blouse	delayed	fiasco	improvise
blunt	deluge	fictitious	impulse
bodily	denounce	field	incubator
boiler	depress	fifty	inhaler
bookie	descent	fill	ink
boon	deterrent	fiscal	innards
bowel	dingy	flexible	insolent
bowling	disc	forensics	internet
breezy	disdainful	formation	intro
brigade	disown	freezing	irritating
bring	dojo	fucker	irritation
bustle	domination	gangland	isolate
capitalize	downriver	ghost	jarhead
casing	dreary	ghostly	jazzy

juniper	original	rely	steadfast	waistline
juror	orthodox	restless	stow	waver
kit	outrage	reverend	strapless	weeds
lament	overview	reverse	streetcar	weekday
leash	pamphlet	rhythmic	strings	willing
leniency	paperback	rich	successor	worthy
liar	patent	ripe	sun	wring
liberating	paycheck	rot	sunset	
ligature	payout	rousing	surf	
lingo	persecute	rusty	surfboard	
loaf	pestilence	samba	survival	
locomotive	phlegm	sanity	tactful	
loophole	pinup	science	tailgate	
lumpy	plume	scrabble	tailpipe	
lust	poetic	scream	teacher	
mainland	poignant	scurvy	telepathic	
mallet	pointer	sedition	textbook	
mantra	portfolio	select	tipster	
matador	potassium	senior	toilet	
medication	prig	serenade	tower	
mineral	principles	serialize	traitor	
mingle	programmer	shave	translator	
mirror	prophecy	shiny	tsunami	
mischievous	prostitute	shoot	typewriter	
misleading	protect	sibling	undetected	
mop	protective	silicon	unexplored	
motorboat	province	skate	unjust	
mule	puck	slam	unorthodox	
mythical	quiver	slate	unpack	
naughty	raccoon	smart	unscrew	
nephew	radar	socialize	unspoken	
nipple	rally	solvent	unwritten	
obligation	random	soup	upward	
observer	reaction	species	vaccine	
olden	reconnect	specimen	valor	
operation	redundant	spinster	valuable	
operator	refuel	splat	vamp	
opium	reggae	squint	veal	
organic	regional	staircase	vegetable	
oriental	reject	statutory	vixen	

Curriculum Vitae

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Honours:

President's List (honour created Fall 2014) Spring 2015-Spring 2016
Awarded to students with a semester GPA of 4.0

Dean's List Fall 2012-Spring 2016
Awarded to students with a minimum semester GPA of 3.4

Awards:

Western Graduate Research Scholarship (WGRS) 2016-present
Awarded to graduate students at the University of Western Ontario.

Charles W. Dobson Memorial Research Award 2016
Awarded to students in Psychology for outstanding original research.

Mary G. Guterba Psychology Student Award 2016
Awarded by faculty to a graduating student in Psychology on the basis of high achievement.

Albert & Adele Krotzer Fund Scholarship 2015-2016
Awarded to students with a minimum GPA of 3.0, a minimum of 64 semester hours completed, and in the College of Liberal Arts and Social Sciences.

Robert G. and S. Ann Berich Maigetter Scholarship 2015-2016
Awarded to students of Geography, Economics, Philosophy, or Political Science with a minimum GPA of 3.0, and based on academic potential, achievement, and financial need.

Gail T. Dennison Scholarship 2012-2013
Awarded to students of Mahoning, Trumbull, and Columbiana counties, and based on academic ability and potential to succeed.

Red and White Scholarship 2012-2016
 Awarded to incoming freshmen with minimum high school GPAs of 3.0 and minimum ACT scores of 22

TEACHING EXPERIENCE

Tutorial Coordinator (Psychology 2800E: Research Methods in Psychology) 2017-2018
 Responsibilities include: Assigning teaching assistants to 2800E tutorial sections; creating/revising lecture and class materials; facilitating conflicts between TAs and students; and responding to questions from teaching assistants.

Teaching Assistant (Psychology 2800E: Research Methods in Psychology) 2016-2017
 Responsibilities included: Lecturing students on basic statistics and research methods in psychology; marking assignments; guiding students on running their own in-class studies and analyzing their data; and assisting students as they wrote up their findings.

THESES

Senior thesis with Matthew Lindberg, PhD (advisor) 2015-2016

“Exploring the role of experiential and cognitive processing in the foreign-language effect”

Examining the presence of changes in cognitive/logical processing associated with decreases in emotional/experiential processing when multilinguals use their less-proficient language.

RESEARCH EXPERIENCE

Lab Manager for Matthew Lindberg, PhD 2015-2016
 Responsibilities included: Corresponding with other lab members; and developing research schedules

Research Assistant for Matthew Lindberg, PhD 2014-2016

“Positive affect, attentional focus, and meaning” 2014

“Metaphors and crime reduction” 2015

“Individual differences in meaning philosophy” 2015-2016

Responsibilities included: Setting up lab; reviewing experimental materials; running participants; and debriefing participants

PRESENTATIONS

Nidel, J. M. & Lindberg, M. J. (2016, May). *Exploring the role of experiential and cognitive processing in the foreign language effect*. Poster presented at the 28th annual convention of the Association for Psychological Science, Chicago.