Configural sensitivity to inter-letter spacing in visual word perception

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The details, data, and analysis for the experiments in this research can be accessible at <https://osf.io/bynvf/>.

Abstract

The word superiority effect refers to the phenomenon that people have better recognition of letters presented within words as compared to recognition of isolated letters. Although many previous research on how the spatial relations between letters in words affect the perceptual processing through the inversion paradigm, a significant amount of effort goes into setting the default inter-letter spacing when designing new fonts. Our current research examines the effect of manipulating letter spacing on the processing efficiency, as a measure of the word superiority effect. First, we tested multiple different words instead of fixed word stimuli to show that measures of efficiency can be generalized; second, we disrupted default inter-letter spacing by increasing, decreasing, and randomizing letter spacing to explore the extent to which the efficiency was sustained with the assessment functions. Our results indicate that participants are limited capacity only in the extreme spacing scenario. Additionally, the principle component (PC) analysis shows that highest PC values occur at normal spacing with degradation with increased disruptionspreading or narrowing. These results appear to confirm the configural nature of perceptual processing with normally-spaced words between identifiable tracking and kerning boundaries, and agree well with the ideas about optimal spacing by type designers and typographers implicit in general notion of “rhythmic spacing”. This work is also notable in that we demonstrate the use of assessment functions as a standardized tool for assessing the capacity benefits and efficiency of configural processing.

Keywords: word perception, word superiority effect, systems factorial technology, processing efficiency

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Introduction

The word superiority effect (WSE) has interested psychological researchers since the early days of the science. The basic finding that people are faster to recognize letters when they are in a word context than when they are alone or in a non-word letter sequence dates back to Cattell (Cattell, 1886). While the effect itself is interesting and the boundary conditions for an empirically measurable effect are informative, the goal of research on this topic is determining what cognitive processes underlie this advantage. Understanding the fundamental mechanism has value in allowing us to integrate the empirical findings into our broader understanding of cognition and perception as well as allowing for more specific predictions of the conditions that lead to better letter (and word) perception to inform practical areas including type design and human factors.

One view on the underlying processes that lead to the WSE is that people have learned the statistical regularities of written language and are able to apply that learning to more efficiently identify letters. For example, identifying a letter on its own requires disambiguating among 26 letters.¹ However, having identified the letter “h” at the beginning of a two letter word, there is far less uncertainty in the identity of the second letter, even without any perceptual information from the second letter. In some cases, the context entirely removes the need for perceptual information. For example, knowing the context “lett_r” removes any uncertainty about the identity of the penultimate letter. Reicher (1969) demonstrated clearly that even when the context is not sufficient to determine the letter identity, letter perception is nevertheless superior in a word context. He achieved this control by limiting the tests to binary decisions between letters that both make valid words, for example querying whether the second letter in “c_re” is an “o” or an

¹ Although based on letter frequency, the uncertainty is lower than a uniform distribution over possible letters.

“a.” Along with a number of variations on the experiment published by Wheeler (1970), these findings that a fully constrained context was not a necessary condition for word superiority.

Another view on the statistical regularities influencing the word superiority effect is that the learned regularities contribute to letter identification through top-down influences in a hierarchical perceptual process. This theory was implanted in the highly impactful “interactive activation model” of visual word perception (McClelland & Rumelhart, 1981). The basic idea of this model is that the learned lexicon would influence the perceptual processing of the letters through activation patterns in a network.

Despite the fact that models like the interactive activation models do quite modeling the word superiority effect, there is evidence that these models may in fact be more efficient with word contexts than human performance would suggest. Pelli, Farell, and Moore (2003) demonstrated that the amount of information necessary to identify a word in noise was highly inefficient and furthermore found that the information needed in longer words approximately tracked the per letter needed information. Based on these data, Pelli et al. suggested that even an independent parallel word recognition system could demonstrate word superiority effects; however, Houpt, Townsend, and Donkin (2014) gave strong evidence against that model.

A related, but distinct approach to modeling the word superiority effect makes explicit connections to general principles of perceptual organization. In particular, these models posit that the word superiority effects are similar to other configural superiority effects in that there are emergent features present in the combination of letters that aid (or are even primary) in identifying the words and hence the letters. These features include parallel lines across letters, e.g., the “t” and “h” in the, as well as the shape of the space between letters. However, letter expertise is different from other expertise in that letter reading is an innate perceptual skill like face perception (e.g. Slater & Kirby, 1998) expertise that achieved by a much wider range of people than other types of visual expertise based on extensive training

(Ericsson, 2017; Ericsson & Lehmann, 1996), e.g. car expertise (Grill-Spector, Knouf, & Kanwisher, 2004), dog expertise (Diamond & Carey, 1986), taxi drivers (Woollett, Spiers, & Maguire, 2009), and chess players (Chase & Simon, 1973). Letters, though formed by lower level features such as stroke and bars, are not perceived in isolation but rather are combined to be recognized as words (c.f. James, Wong, & Jobard, 2010).

The configural processing view (see Maurer, Le Grand, & Mondloch, 2002, for a review) has been tested in various formats in expertise object perception — e.g. inverted images of faces or dogs (Diamond & Carey, 1986), top half upside-down for car images (Gauthier, Curran, Curby, & Collins, 2003), and even composite faces and gestalt line patterns (Curby & Moerel, 2019). Many of these studies focused how changes in configural structure induced less effective object processing, indicating that configural processing can also play an important role in word perception. On the other hand, word perception displays different characteristics compared to other expertise object recognition. Wong and Gauthier (2007) explored whether the subordinate level advantage exists in the face perception (e.g. “Bill Clinton” rather than “A Caucasian male”; Tanaka, 2001). Their results indicated that face perception requires categorization at subordinate level, whereas letter perception involved mainly basic-level categorization (e.g. “K” rather than “a handwritten k”). Ge, Wang, McCleery, and Lee (2006) further tested the configural information embedded in the character, concluding that Chinese characters as word perception did not significantly show inversion effect (but see Kao, Chen, & Chen, 2010, for the different argument).

While much previous research has linked configural sensitivity of word perception – as face-like object – to inversion effect (e.g. Luo, Chen, & Zhang, 2017; Wong, Wong, Lui, Ng, & Ngan, 2019), a more practical configural feature is the spacing among letters within a word. Indeed, a significant amount of effort goes into setting the default inter-letter spacing when designing new fonts.

This brings us to the goal of the current project, examining the degree to which

disrupting these emergent features reduces or eliminates the word superiority effect. In the following series of experiments, we modulate the space between letters in various ways and test the degree of word superiority using the capacity coefficient, which we explain in more detail below. In particular, we either spread or squeeze the font specified spacing between letters. We also manipulated whether the change in spacing was consistent across pairs of letters in a word or varied across bigrams. This last manipulation connects to another principle of perceptual organization, grouping. If, within a word, two letters are close together while the rest are further apart, grouping based on proximity cues might suggest that the full string may not be interpreted as a single group, hence slowing the perceptual process.

In the next section, we give a brief overview of the literature on the inter-letter spacing. Then, we describe the capacity coefficient including its previous applications to word superiority effects. Once we have established the measure, we detail our experiments one-by-one, followed by an overall discussion.

Inter-letter spacing as configural information

Among many models on exploring mechanisms contribute to the superiority effects, one of the most well-known models on the word superiority effect is the Interactive-Activation Model (IAM; McClelland & Rumelhart, 1981; Rumelhart & McClelland, 1982). IAM hypothesized that word perception process was comprised of a hierarchical network of information at the level of feature, letter, and word. Each relevant unit in the system is an entity called a “node” and nodes are organized into levels. Nodes are connected with its “neighbors” in two different ways: excitatory and inhibitory. The word superiority effect, therefore, comes from the excitatory from word-level nodes to letter-level nodes in a top-down manner: word information reactivates letter information. In the given simulated example, the model illustrated that how the letter “k” over-performed the alternative candidates of “r”, “d”, which in return successfully activated

word “work” instead of “word”, “weak”, and “wear” when presented with the first three letters “wor_”. Though IAM showed its strength in computational tracking the superiority effect, the model failed in drawing conclusions on many other word perception observations. One of these arguments was that it ignored the fact that observers used extra-letter visual information (e.g. Gomez, Ratcliff, & Perea, 2008; Mewhort & Johns, 1988)

Both configural and non-configural extra-letter information influences word perception. The non-configural information includes syllables (pronounceable or non-pronounceable strings; e.g. Baron & Thurston, 1973; Estes & Brunn, 1987), word frequency – word familiarity influenced letter identification through an extra memory loading process (e.g. Allen & Madden, 1990; McClelland & Johnston, 1977), and structural features such as transposed letter positions (e.g. “trial – trail”; Gomez et al., 2008; McClelland, 1976), mixed cases (e.g. “gArDeNeR”; Mayall, Humphreys, & Olson, 1997), and font (Sanocki, 1987; Sanocki & Dyson, 2012).

Our current research focused the configural information of the inter-letter spacing, which is critical for letter legibility (Bouma, 1970; Martelli, Majaj, & Pelli, 2005). However, previous research has shown controversial evidence in answering this whether further inter-letter spacing facility word processing. Johnston and McClelland (1974) reported that when instructed to attention to the whole words subjects were more accurate in the identification when instructed to only focus on letters, which might due to the critical letter in the whole words fell further away from the center of the fovea. In a series of experiments focused on discussing pseudo-word perception, Mewhort, Marchetti, and Campbell (1982) hypothesized that the subjects’ sensitivity to spacing was due to that spacing being treated as a symbol that typically marked the ends of a word in a string of text. However, the effect of spacing was task dependent (Campbell, 1985): participants were faster if the stimuli displayed simultaneously with extra spacing between letters while if the display was successive, the extra spacing resulted in slower response times.

A more recent study by Perea and Gomez (2012) found that slightly wider inter-letter

spacing than default inter-letter spacing facilitated the response times in identifying whether the string was a word or non-word. Additionally, the effect of inter-letter spacing show a decreasing linear trend — the response times decreased as inter-letter spacing varied from condensed to expanded. The effect of inter-letter spacing was presumably due to less crowding or a more accurate letter-position-coding process. Furthermore, McLeish (2007) reported that increased letter spacing may be beneficial to low-vision readers and Zorzi et al. (2012) showed that a simple manipulation of inter-letter spacing substantially improved text reading performance on dyslexic children. Nevertheless, the increased inter-letter spacing clearly can negatively affect word perception. As Perea, Moret-Tatay, and Gómez (2011) noted in the discussion: “an increase of inter-letter spacing beyond a certain limit may not only hinder a word’s physical integrity, but also the distance of the letters from the center of the fovea so that retinal acuity is reduced.” Importantly, there is other evidence showing that reading does not benefit from increased inter-letter spacing (Chung, 2002), which may be due to changes in the effective visual span size (Yu, Cheung, Legge, & Chung, 2007).

To summarise, previous research has established that there is a relationship between configural information of inter-letter spacing and word perception. However, it was uncertain in which scenario the the inter-letter spacing would facilitate word perception. One issue that we address with the current research is the use of a consistent, process model based, measurement of word perception efficiency. Prior work either focused on accuracy only (Johnston & McClelland, 1974; Mewhort et al., 1982) or emphasized more on response times (Perea & Gomez, 2012; Perea et al., 2011) while the study on reading explicitly concentrated on reading speed that calculated through word exposure duration. We discuss in the next section about quantitative efficiency measures.

Measuring Word Processing Efficiency

In the early research on word perception by Cattell (1886), the word superiority was observed through a shorter reading time for letters that had no connections compared to letters which built as words. The finding triggers an interesting research direction that reading a series of letters that can be combined as a word is faster than random letters strings. While the initial observation was about letter process time, the later revival of word perception research during the 70s and 80s did not settle down the puzzle of an unified measurement of “superiority”: most considered process efficiency as subjects recognized word with a higher probability of being correct than they had on a single letter alone (e.g. Purcell & Stanovich, 1982; Reicher, 1969; Wheeler, 1970). The common experimental paradigm, was to present subjects with a string of letters for a short period and then asked subjects to identify the critical letter. There was only a few word perception research also included the discussion of response times (e.g. Allen & Madden, 1990; Campbell, 1985). For example, Johnson, Allen, and Strand (1989) found different effects of word frequency on lexical identification response times — subjects took longer to identify the medium-frequency words than high- or low- frequency words. On the other hand, many more recent studies took both aspects of accuracy and response times into consideration without a strict comparison between letter and word identification (e.g. Perea & Gomez, 2012; Perea et al., 2011).

Pelli et al. (2003) proposed a way of assessing human performance of “efficiency” as the ratio of the ideal’s threshold energy to the human observer’s: the fraction of energy that used by the observer that was ideally required to account for the observer’s measured performance. Here, the contrast energy is the integral of the squared signal contrast over the extent of the stimulus. Pelli et al. found that in comparison to a strictly letter-based observer which utilized the identification of tentatively identified letters and then choose the probably word from the list of alternatives, human’s word performance never exceeded the letter-based bound. Their results indicated that participants may follow the strictly

letter based identification, the advantage of word superiority effect was subtle.

Houpt, Townsend, and Donkin (2014) proposed the capacity coefficient for quantifying word processing efficiency, to complement accuracy-based measurement of efficiency. Instead of focusing on whether the letter has been identified correctly within the word context or not, the capacity coefficient takes a different perspective. The measure takes an estimated time to discriminate each letter in a word then predicts how long a the full word would take to discriminate under the assumption that the letters are perceived independently and in parallel. Based on the relative performance to baseline, participants' performance can be categorized into three levels: super capacity (faster than the predicted baseline), unlimited capacity (approximately equal to the predicted baseline), and limited capacity (slower than the baseline). We refer readers who are interested in knowing more details about capacity coefficient to previous related research (e.g. Houpt, Blaha, McIntire, Havig, & Townsend, 2014; Houpt & Townsend, 2012). A word superiority effect in terms of the capacity coefficient would be supercapacity, implying an advantage over independent parallel perception of letters for word contexts, and higher capacity coefficient values for words than non-words. Houpt, Townsend, and Donkin (2014) showed that capacity coefficient to quantify both word superiority effect as well as pseudo-word superiority effect, which assumes that participants are more accurate in the word context if a sequence of letters conformed to the pronunciation rules. Their results also indicated the inefficiency processing of the word when the holistic processing failed such as non-word, upside-down, and katakana (for native English speakers).

Current Work

In addition to the new methodological approach, our current research extends the previous work of Houpt, Townsend, and Donkin (2014) by jointly analyzing response times and accuracy for quantifying word processing efficiency using a variant of the capacity coefficient, the assessment functions, $A(t)$. Assessment functions have a similar underlying

theory as capacity coefficient, comparing the performance with the predicted baseline of unlimited-capacity, independent, parallel (UCIP) model. The UCIP model makes a prediction of unlimited capacity that $A(t) = 1$. Alternatively, if the assumption is violated, participants may either have limited ($A(t) < 1$) or super ($A(t) > 1$) efficiency relative to the baseline. We refer readers who would like to know more about technical details of assessment functions the work by Townsend and Altieri (2012).

We hypothesize participants would process word with the normal letter spacing efficiently (Experiment 1). The slightly wider inter-letter spacing will facilitate the processing efficiency as it reduces the letter position uncertainty and the slightly squeezed inter-letter spacing will induce the processing inefficiency as a result of visual crowding (Experiment 2). Moreover, the too wide or squeezed inter-letter spacing would significantly reduce the processing efficiency due to the non effective visual span (Experiment 4). In addition, the influence of configural sensitivity processing efficiency can also be achieved through the inconsistency in spatial information (Experiment 3). In general, we hypothesize an inverted “U-shape” relationship between the increased inter-letter spacing and processing efficiency and a linear decreasing between the squeezed inter-letter spacing and processing efficiency. We expect that the observation of various efficiency would be revealed through our tool of using assessment functions that consider both accuracy and response times.

Method

Participants

We targeted recruiting 50 subjects for each experiment. Participants were recruited from the Wright State University undergraduate subject pool and participated for course credits. All participants reported having no difficulty reading or understanding English, and normal or corrected to normal vision. Participants were excluded in data analysis if their performance under accuracy of 80%. A table of the age and gender information is

included in the Appendix (Table 1).

Experimental Design

Our study employed the same experimental paradigm as Houpt, Townsend, and Donkin (2014) except a few minor changes in the stimuli adoption. In Houpt, Townsend, and Donkin (2014), the targets and foils were the same throughout the experiment within each condition. In the current study, words were chosen randomly from a dictionary of four letter words based on the criterion that a letter in any position could be changed to at least one other letter and still result in a word. Additionally, unlike Houpt, Townsend, and Donkin (2014), we only ran word conditions, not pseudo-words, non-words, or unfamiliar character string conditions.

The task was consisted of two sessions. In the first session, participants were required to identify whether two successive words were same or different. The second word was either the same (i.e. targets) or generated using one letter replaced in the first word to produce the *different* words (i.e. distractors). Each word was four letters. We did not use words longer than four letters because there were not five letter words with which this single letter morph in each position would result in a word.

For example, if the target word was “come,” the second word could either be “come,” or “home,” “came”, “code,” “coma” by replacing any of the four letters in the first word. In the second part, participants only were asked to identified if the two letters were the same or not, i.e. the target letters in the words comparison (“c – h” for “come – home”). All words were consisted of four letters presented in the Arial font on a gray blank background².

² Our original intention was to use the Williams Caslon font and its inter-letter spacing in our experimental design. Unfortunately, due to a coding error, we used the default font Ariel instead. We admit the possible subtle differences of default inter-letter between the Williams Caslon and employed font, however, we believe that wrong implemented font design does not fundamentally change our observation and interpretation.

Figure 1. The stimuli in *narrow* and *spread* Experiment 2 that compared to the normal spacing

There were four experiment conditions that varied inter-letter spacing in our current study: Experiment 1 is a simple replication of the previous study by Houpt, Townsend, and Donkin (2014) with the updated stimuli design. Experiments 2 through Experiment 4 were dedicated to manipulating the inter-letter spacing. Experiment 2 included two inter-letter spacing conditions: *narrow* and *spread*. In the *narrow* condition, spacing between letters in the word was 70% of the normal spacing; in the *spread* condition, spacing between letters was 200% of the normal spacing. Experiment 3 further extended the inter-letter spacing variability: inter-letter spacing (randomly drawn from 70% to 200% each trial) was either equally spaced but varied in two successive words (*between*) or unequally spaced for a single presentation (*within*). Experiment 4 tested two extreme inter-letter spacing conditions: 50% (*extreme narrow*) or 800% (*extreme spread*) of the normal spacing. The Experiment 2 and Experiment 4 were within subjects designs — subjects performed both normal spacing condition and abnormal spacing condition.

Procedure

The experiments were programmed using PsychoPy (Peirce, 2007). Word stimuli were presented on a monitor with the resolution of 1280×1024 pixels and a refresh rate of 85Hz.

Figure 2. The stimuli in *within* condition in Experiment 3 and two extreme conditions in Experiment 4

As depicted in Figure 3, each trial start with the first word stimulus appeared 1000ms with the mask of strings below the word, then the successive stimulus for comparison showed up for 200ms in which the spacing was varied. After the words stimuli presentation, the string mask would appear for another 1000ms and then the screen turned blank till the trial ended. Participants were asked to respond accurately and quickly as possible by pressing the button box indicating whether the two stimuli were same or different.

Each participant performed 700 trials total. In Experiment 1 and Experiment 3, trials were evenly split into word comparison trials and letter comparison trials. In Experiment 2 and Experiment 4, participants performed the 350 trials in the abnormal spacing session and 350 trials in the normal spacing sessions with each of them had same trials in word and letter comparison. All participants performed word session first then followed by the letter session. Participants in the Experiment 2 and Experiment 4 were randomly assigned to start with normal spacing or abnormal session.

Figure 3. The trial of a word session in the Experiment 1. The spacing of stimuli word was regular.

Results

We report our observed results in two parts. In the first part, we report the behavioral data in accuracy and response times. All behavior data analysis were conducted using R statistical software (R Core Team, 2019). The Bayesian repeated measures ANOVA used BayesFactor package (Morey & Rouder, 2018). Assessment functions were analyzed through sft package (Houpt, Townsend, & Donkin, 2014).

The results of Bayesian ANOVA were interpreted based on model comparisons between models including or excluding the independent variables of interest, of which Bayes factor indicates the relative support likelihood of the observed data under two alternative models. For example, if $BF = 3$, the observed data are three times more likely to have occurred under one model relative to the other model. For qualitative interpretation of the Bayes factor scale, we followed the category of evidential strength

summarised by Lee and Wagenmakers (2014)³. We first reported the most likely model that compared to the baseline model only included the intercept of subject variances. Then we reported the BF comparisons of the most likely model to alternative models to report the relative evidence of the observed effect. To illustrate the effects of experimental manipulations, we reported the posterior distribution using based on full model, which included all main factors and their interactions. The posterior distribution gives the estimation of relative plausibility of different parameter values (c.f. McElreath, 2020). For each posterior distribution, we present 95% high density interval (Meredith & Kruschke, 2018) that was a range of posterior distribution, indicating that the interval was 95% likely to include the true value of the parameter (Lee, 2018).

RT/Accuracy Analyses

Experiment 1: Replication. The Bayesian ANOVA indicated that the most likely model of accuracy included both main effects of session and stimulus type, $BF = 7.02 \times 10^{205}$ over the null model, which included only variation among subjects as a factor. There was only an anecdotal support for the best model relative to the second best model which included the additional interaction between stimuli session and type ($BF = 2.52$). The posterior distribution (Figure 4, left column) indicated that subjects were more accurate in responding to distractors (higher correct rejection rate) compared to targets (hit rate) in the letter condition but that the difference was suppressed in the word condition.

The Bayesian ANOVA showed that the most likely model of response times included a main effect of stimuli session and stimuli type, as well as their interaction ($BF = 2.42 \times 10^9$ over the null model). There was also strong evidence favor it over the second best model that excluded the interaction ($BF > 3.62 \times 10^3$). The posterior distribution (Figure 4, right

³ $BF \in (1, 3]$: anecdotal evidence, $BF \in (3, 10]$: moderate evidence, $BF \in (10, 30]$: strong evidence, $BF \in (30, 100]$: very strong evidence, $BF > 100$: extreme evidence

column) indicated that subjects were slower in responding to the words sessions compared to the letters sessions. Furthermore, subjects spent longer time to respond to distractors in both words sessions and distractor sessions.

Figure 4. The posterior distributions of response times and accuracy in Experiment 1. The bar represented 95% HDI for each posterior distribution and the dot represented the median

In Experiment 1, we found same pattern in Houpt, Townsend, and Donkin (2014) that subjects spent longer time in sessions of letters than words. The Bayesian ANOVA on accuracy indicated the best model included the main effect of session, a clear evidence against WSE that subjects failed to perform more accurately in words sessions.

Experiment 2: Spread/Narrow. Figure 5 depicts posterior distributions of subjects' responses in the *narrow* condition where the abnormal inter-letter spacing of words were 70% of the normal spacing. The Bayesian ANOVA on accuracy indicated that the best model included all three main effects and the interaction between spacing and

session ($\text{BF} > 1.57 \times 10^{28}$ over the null model). There was only marginal evidence for the best model of accuracy over the second best model ($\text{BF} = 1.03$), which excluded the interaction. Likewise, the results on response times indicated that the best model included all three main effects and the interaction between spacing and session ($\text{BF} > 4.95 \times 10^{129}$ over the null model). There was strong evidence of that model relative to the second best model, which included additional interaction of spacing and stimuli ($\text{BF} = 9.58$). Overall, there was an effect of spacing — compared to the normal spacing, subjects were slower in responding to distractors in the abnormal spacing.

Figure 5. The posterior distribution of response times and accuracy in Experiment 2 of *narrow* condition. The bar represented 95% HDI for each posterior distribution and the dot represented the median

Figure 6 depicts posterior distributions of subjects’ response times and accuracy in the *spread* condition where the inter-letter spacing of words were 200% of normal spacing in the abnormal settings. The Bayesian ANOVA on accuracy indicated that the best model only included the main effects of session and stimuli ($BF > 2.11 \times 10^{16}$ over the null model). There was strong evidence of it over the second best model, which included the additional interaction between stimuli session and stimuli type ($BF = 24.7$). For response times, the best model indicated the main effects of spacing, session, stimuli with the additional interaction between spacing and session ($BF > 1.28 \times 10^{103}$ over the null model). There was moderate evidence of the best model favor of it over the second best model, which included the additional interaction between stimuli and spacing ($BF = 3.95$).

We tested the effect of inter-letter spacing on subject’s responses in Experiment 2 by varying the normal inter-letter spacing a little to make it slightly “spread” or “narrow”. As expected, the manipulation of spacing was included in the best model for both response times and accuracy in *narrow* condition and response times in *spread* condition. It is noticeable that results indicated that the best model for accuracy in the *spread* condition did not include the spacing effect. This suggested that subjects tried to maintain high accuracy with the sacrifice of response times. In addition, our results also showed that these best representative models that included the main effect of spacing also included the interaction of spacing and session, this matches our experimental design that spacing was only expected to influence subjects’ visual processing with words.

Experiment 3: Between/Within. The Bayesian ANOVA indicated that the best model of accuracy included the main effects of stimuli session and stimuli type ($BF > 1.71 \times 10^{22}$ over the null model), and a strong evidence of it favored over the second best model which also included the interaction between stimuli type and stimuli session ($BF = 18.44$). The results on response times indicated same pattern: the best model included the main effects of stimuli session and stimuli type ($BF > 2.68 \times 10^{180}$ over the null model). There was strong evidence over the second best model which included the

Figure 6. The posterior distribution of response times and accuracy in Experiment 2 of *spread* condition. The bar represented 95% HDI for each posterior distribution and the dot represented the median

additional interaction between stimuli session and stimuli type ($BF = 36.95$).

The Bayesian ANOVA on response times in the *between* condition showed that the best model included main effects of stimuli type and stimuli session ($BF = 3.43 \times 10^{118}$ over the null model). There was strong evidence against the second best model which included an additional interaction between stimuli type and stimuli session ($BF = 28.06$). For accuracy, the most likely model included main effects of stimuli type and stimuli session ($BF > 4.58 \times 10^{17}$ over the null model). There was strong evidence of it against the second best model with the additional interaction between stimuli session and stimuli type

Figure 7. The posterior distributions of response times and accuracy in Experiment 3 of *within* condition. The bar represented 95% HDI for each posterior distribution and the dot represented the median

(BF = 38.19).

Compared to the previous experiment, we added more “uncertainty” in Experiment 3 — the inter-letter spacing was not fixed each trial. Instead, they were varied across trials (*within*) or unequally spaced over trials (*between*). Our initial thought was that if the word identification was more accurate than letters as reported in WSE findings, the variation of inter-letter spacing within/between the word(s) would reduce the accuracy. However, we found similar results as Experiment 1 that there were two main effects of stimuli and sessions — subjects’ responses were more accurate and faster in letters identification than words identification (Figure 7 and Figure 8).

Experiment 4: Extreme. Experiment 4 tested subjects’ responses in the “extreme” inter-letter spacing scenario. When the inter-letter spacing was extremely

Figure 8. The response times and accuracy in Experiment 3 of *between* condition. The bar represented 95% HDI for each posterior distribution and the dot represented the median

narrow (50% of the normal spacing), the Bayesian ANOVA results indicated that the best model on accuracy included all main effects (spacing, stimuli, session) and the interaction between spacing and the other two effects, respectively ($BF > 2.66 \times 10^{107}$). There was only moderate evidence of favoring it over the second best model, which excluded the interaction between spacing and stimuli ($BF = 2.13$). The best models on response times included all three main effects and the interaction between spacing and session ($BF > 4.95 \times 10^{129}$ over the null model). There was strong evidence of it against the second best model which also included the additional interaction between session and stimuli ($BF = 11.86$).

When the inter-letter spacing was extremely spread for subjects to compare (800% of the normal spacing), the best model on response times included all three main effects and the interaction between the spacing and session ($BF > 5.30 \times 10^{261}$ over the null model). There was also moderate evidence against the second best model which also included the

Figure 9. The response times and accuracy in Experiment 4 of *extreme narrow* condition. The bar represented 95% HDI for each posterior distribution and the dot represented the median

interaction between session and stimuli ($BF = 11.86$). The best model on accuracy was the full model that included all main effects and combinations of all possible interactions ($BF > 1.08 \times 10^{182}$ over the null model); it was favored over the second best model, excluded the three-way interaction, with strong evidence ($BF > 5.97 \times 10^5$).

The Experiment 4 tested two extreme cases, either letters overlap so subjects need to take a lot of effort to identify each letter (50% of normal spacing), or letters were further away so subjects would need to make multiple eye movements to locate the letters (800% of normal spacing). In the *extreme narrow* condition, we observed the interaction between

Figure 10. The response times and accuracy in Experiment 4 of *extreme spread* condition. The bar represented 95% HDI for each posterior distribution and the dot represented the median

spacing and session on response times and accuracy. In addition, there was also an interaction between spacing and session on accuracy. We found that subjects were less accurate in responding to targets (low hit rate) in the normal spacing condition – about the same level as the extreme words (Figure 9). In the *extreme spread* condition, the model on accuracy again indicated that spacing interacted the other two main effects and there was also an interaction between the three. The posterior distribution displays that compared to distractors, responses to targets were less accurate in the normal condition whereas they were more accurate in the abnormal condition (Figure 10).

Efficiency Analyses

Assessment Functions. Figure 11 depicts the assessment functions across the four experiments in which each line represents an individual subject’s performance. The average group in Experiment 1 obtained a better performance than predicted baseline, which indicated a super capacity. Therefore, our results replicated the efficiency capacity coefficient reported by Houpt, Townsend, and Donkin (2014) with variation in the target word and with accuracy taken into consideration. The top right of Figure 11 depicts the results for Experiment 2, with half the subjects experiencing twice normal spacing and half experiencing 70% of normal spacing, and both groups viewing normally typeset words. Subjects in all conditions were super capacity, and there was a weak trend that subjects were more efficient in the normal spacing condition than in the abnormal spacing conditions.

In Experiment 3, performance in both groups was better than predicted baseline. The figure also indicated that subjects were likely to be more efficient when letter spacing varied within a word relative to when spacing was consistent within a word but varied across trials. We suspect that the *between* condition included more “uncertainty” as subjects need to adjust to inter-letter spacing of the second word when comparing successive words. In the final experiment, with the most extreme inter-letter spacing, subjects were limited capacity in the extreme spread (800% of normal spacing) and extreme narrow (50% of normal spacing) conditions where much effort had been taken into identifying each letter within the word.

To summarise our findings in assessment functions, although we explored various inter-letter spacing designs across multiple experiments, subjects still process words efficiently compared to the predicted baseline obtained from processing individual letters. Instead, subjects were only limited capacity in the extreme spacing scenarios of Experiment 4.

fPCA. The assessment functions $A(t)$ do not have well-defined, associated inferential statistical tests. Rather than rely solely on visual inspection, we investigated our manipulations using function principle component analysis (Burns, Houpt, Townsend, & Endres, 2013).

Figure 12 shows the variation in of two a two-dimensional representation, after a PCA reduction and varimax rotation, of the assessment functions across participants, manipulations, and experiments. In both panels, the variation across subjects within a condition is represented by a box plot embedded within a violin plot to summarize the mean, quartiles, and overall shape of the distribution. In both dimensions, the normal letter spacing (1 on the x-axis) is the highest distribution, with decreasing values as the spacing became more extreme. Interestingly, the distributions on both dimensions of the between-trial spacing variation and the within-trial variation were not particularly different, nor noticeable lower than the normal spacing. A Bayesian ANOVA on the component scores indicated that there is strong evidence for an effect of the spacing condition on the first ($\text{BF} > 9.87 \times 10^9$) and second dimension ($\text{BF} > 8.74 \times 10^3$).

Discussion

Contrary to the traditional WSE that subjects were more accurate in words comparisons, our behavioral results showed that subjects had more difficulty in word comparisons compared to letter comparisons. Subjects spent more time and had less accurate responses in word comparisons.

We tested different inter-letter spacing sessions through Experiment 2 to Experiment 4. As expected, the abnormal spacing slowed subjects down and led to less accurate answers in word comparisons. In Experiment 2, the lightly spread or narrow inter-letter spacing affected subjects' performance. In Experiment 3, the inter-letter spacing was not equally spaced between or within trials and we did not find such disruption slowed down or decreased accuracy compared to subjects' performance in Experiment 1. The effect of

inter-letter spacing manipulation was most dramatic in Experiment 4, in which were the most extreme spacing conditions. Across experiments, results indicated relatively consistent results for response times, but there was more variation in which model was the best for accuracy. Thus even though the subjects were instructed to respond accurately and fast as they could, subjects could treat responses differently — either slow but accurate or fast at the cost of accuracy — subject to alternations of inter-letter spacing. In addition, our analyses also separated stimulus type and found that subjects responded differently to distractors and targets, intuitively responding to distractors should be faster since subjects could say “no” as soon as they identified there different letter whereas correctly responding “yes” required the subject to check all of the letters. Though it is an interesting topic to test whether subject terminate the trial immediately when they noticed any difference or they chose to finish process all letters before making their responses, directly testing the stopping rule is not feasible with our design.

Assessing efficiency with both accuracy and response times into consideration, we found that consistent with previous research (Houpt, Townsend, & Donkin, 2014), subjects efficiently processed words with variation in stimuli (non-repeated different stimuli) and spatial information (narrow or spread) except for the extreme conditions compared to the predicted baseline. Our results further indicated an ordered relationship between spacing and efficiency: subjects were more efficient in responding to words in normal spacing compared to abnormally spaced words (Experiment 2 and Experiment 4); and this efficiency is also related to the “uncertainty” in spatial information (Experiment 3). The fPCA test also indicated that the normal spacing has highest scores in both dimensions with all manipulations analyzed.

General Discussion

In the current research, we tested subjects’ sensitivity to the configuration of printed words by manipulating inter-letter spacing. Without accounting for the fact that correctly

identifying words requires the correct identification of multiple letters, our results suggested that subjects' performance was not consistent with *traditional* WSE hypothesis; subjects were more accurate with letters than words across a number of conditions. Moreover, subjects' word identification accuracy was affected by inter-letter spacing disruptions, indicating a potential for speed-accuracy trade-offs. To more thoroughly examine the affect of spacing on the word superiority effect, we used assessment functions (Townsend & Altieri, 2012), which account for speed-accuracy trade-offs and the fact that words require more correct letter identification. By using the assessment functions, we found subjects' efficiency stayed relatively high across a range of inter-letter spacing disruptions – increasing spacing, decreasing spacing, and randomizing spacing between and within words. Subjects were only limited capacity, i.e. less efficient with letters in words than with letters alone, in the extreme spacing scenario. The additional fPCA analysis showed that there is strong evidence an influence of letter spacing on efficiency and that the assessment functions were largest with normal spacing.

In addition to the comparative efficiency in word processing to the formed baseline, our current study also adds new evidence on the relative performance across different inter-letter spacing conditions. In contrast to our hypothesis that the slightly wider inter-letter spacing would facilitate word processing efficiency (McLeish, 2007; Perea & Gomez, 2012), our results indicate that subjects were not more efficient in processing words with increased inter-letter spacing (200%), suggesting the reduced letter position uncertainty is not sufficient to contribute to processing efficiency. On the other hand, we found that decrements in efficiency with squeezed inter-letter spacing (100%), and even more limited performance with extreme spacing (50% and 800%) conditions. Such finding supports previous findings that word processing are influenced by effective visual span (Chung, 2002; Perea et al., 2011; Yu et al., 2007). Together, our research suggests that subjects were most efficient with normal spacing compared to other types of inter-letter spacing settings. Future research can also investigate whether if there is a intermediate

point between normal and 200% of normal spacing to test the efficiency changes in further. It is also possible that the efficiency gains from slightly wider spacing may particularly apply to the group of subjects with difficulty in reading (Houpt, Sussman, Townsend, & Newman, 2015; Zorzi et al., 2012).

Our introduction of assessment functions provides a feasible tool in bridging the word perception research and other object perceptual expertise research. Most perceptual expertise research, represented by face perception, examines object feature processing in two aspects: obligatory attention to all parts and configural sensitivity (c.f. Wong et al., 2019). While we adopt inter-letter spacing to test configural sensitivity, the assessment functions can also be modified to test the word perception processing in other form of perceptual task such as composite task (e.g. obligatory attention to all parts) and inversion paradigm. More importantly, the use of assessment functions allows us to overcome restrictions of limited stimuli by employing various word stimuli. In effect, most previous word perception studies only examined processing with a fixed set of stimuli (e.g. Wong et al., 2012; Wong & Gauthier, 2007). Therefore, it is unknown whether the observed effects were due to the selected stimuli (e.g. Hsiao & Cottrell, 2009) or a more generalized configural feature (e.g. Luo et al., 2017). Given that human as object expertise have unlimited sources access to perceptual objects in our daily life (e.g. Sunday, Patel, Dodd, & Gauthier, 2019), we believe our work presents an example to how the assessment functions can be implemented in other language systems (e.g. Chinese, Hebrew) in other more applied scenario.

In summary, our current research introduces assessment functions in measuring WSE by jointly analyzing accuracy and response times. We established the relationship of processing efficiency and configural sensitivity to inter-letter spacing. Our results indicate that subjects stay relatively high efficiency with non-fixed word stimuli set. Moreover, the efficiency sustains across various disrupted (increasing, decreasing, randomizing) inter-letter spacing conditions. Subjects only perform limited capacity in the extreme

spacing scenario and they process words most efficiently at the default normal setting. We believe our findings are valuable for understanding the role of inter-letter spacing in the word perception processing and offer possibilities in using assessment functions to explore other configural information that contributes to word perception in the future research.

Acknowledgment

The data in the research were collected when both first two authors were at Wright State University. We would like to thank Jordan Melas and research assistants at the Mathematical Modeling of Human Performance Lab for supporting data collection for this study.

Figure 11. Assessment function indicating the group average, the results indicated that subjects are limited capacity only in the extreme spacing scenario (the left bottom)

Figure 12. The values of principle component analysis, based on inter-letter spacing conditions

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Table 1

The demographic information subjects.

Experiment	Total	Gender				Age
		Male	Female	Unknown	Other	
1	75 (25)	33 (10)	40 (1)	1 (1)		[18,32] ([18,23])
2	61 (11)	10 (1)	51 (11)			[18,34] ([18,22])
3	56 (6)	38 (3)	16 (3)	1	1	[18,37] ([18,33])
4	67 (17)	48 (6)	18 (11)			[18,56] ([18,28])

Note. Details of excluded subjects are given in parentheses.