Won't you be my neighbor: Investigating the levels of typed language production through neighborhood density

A thesis submitted by

Ann Kochupurackal

in partial fulfillment of the requirements for the degree of

Master of Science

in

Psychology

Tufts University

May 2024

Advisor: Dr. Ariel M. Cohen-Goldberg

Abstract

From an empirical and theoretical perspective, co-activation of multiple linguistic representations can arise at any stage of language processing and can affect the activation, retrieval, and production of a target. Neighborhood density has been used to investigate lexical processing (Hameau et al., 2021; Sadat, Martin, Costa, & Alario, 2014). The purpose of this thesis was to use neighborhood density to investigate the levels of processing in typed language production. We hypothesized that different types of neighbors (i.e., position-dependent and position-independent) could index different levels of processing. Using a picture naming task, we found evidence to suggest that position-specific representations are only seen at later stages of processing. The findings of this study help create a more comprehensive account of serial order planning in typed language production.

Acknowledgements

In this journey of creating this Master's thesis, I've been fortunate to have the support and encouragement of incredible individuals who have made the adventure of those academically and reaching, and personally rewarding. I am very grateful for the guidance and feedback of my committee – Dr. F-Xavier Alario, Dr. Gina Kuperberg, and Dr. Ariel M. Cohen-Goldberg. A special shoutout to my advisor, Ari Cohen-Goldberg, for his infinite patience and willingness to discuss the ins and outs of every aspect of the experiment. And a big thank you to my lab mate & research assistants for commiserating and working with me through it all.

To my family and friends, thank you for being my cheering squad, understanding my occasional thesis-induced quirks, and celebrating both the small victories and the major milestones.

Table of contents

List of tables

List of figures

List of abbreviations

Neighborhood density - ND

Response times - RT

Phonological ND - PhND

Orthographic ND - OrND

Inter-keystroke interval - IKI

Won't You Be My Neighbor: Investigating the levels of typed language production through neighborhood density

The parallel activation of multiple related or similar representations is a central tenet of parallel distributed processing models of cognition (McClelland, 1993; Rumelhart, et al., 1986) and has been particularly important in models of language processing (Dell, 1986; Levelt, Roelofs, & Meyer, 1999). *Lexical neighbors* refer to words that share a similar phonological or orthographic structure to a target word and are often used to study lexical access, or how the similarity of words in their form or sound affects processing. A word's neighbors are defined as the set of different words that are created by changing one letter of a word (via substitution, deletion, or insertion) while maintaining letter positions (Coltheart, Davelaar, Jonasson, & Besner, 1977). The target word BAG, for example, has phonological neighbors such as BADGE, BAR, BAT, and RAG, all of which differ from the target by one sound; its orthographic neighbors differ from the target word by one letter, such as BAR, BAT, and RAG. A word's *neighborhood density* (ND) is the sum of its neighbors and is a quantitative measure of its phonological or orthographic similarity to other words in the lexicon. In this study, ND will be used to investigate the stages of the planning and processing that takes place during language production.

Research regarding how ND affects production has had mixed results, with the current consensus being that neighbors inhibit spoken production. Sadat, Martin, Costa, and Alario (2014) used a spoken picture naming task to investigate the effect of phonological ND (PhND) on response times (RT). Their analysis yielded results that showed PhND have an inhibitory effect on RT, i.e., that participants named a target word with a larger PhND more slowly than they did a target word with a smaller ND. They also found that absolute *onset density*, or the number of neighbors that share the same onset consonant with the target word yielded insignificant results. Notably they found that a stronger inhibitory ND effect was found in faster participants. Lastly, they found there were no significant effects of ND on accuracy.

In addition to the results of their experimental analysis, they also reanalyzed studies that had found facilitative effects of PhND (Baus et al., 2008; Pérez, 2007) and did not find the same effects. Under finer-grained analyses to control confounding variables, the data of Pérez (2007) even observed an inhibitory effect. Other studies have also found an inhibitory effect of PhND on naming latencies (Arnold et al., 2005; Gordon & Kurczek, 2013; Vitevitch & Stamer, 2009). Therefore, in spoken production, there is a growing amount of evidence to suggest that neighbors slow processing.

While there have been numerous studies investigating the effects of ND in spoken production, much less work has been done on how it affects production in other modalities. Sehyr & Emmorey (2022) appears to be the only study that has examined ND in sign language production. They used a picture naming task to examine lexical retrieval in American Sign Language (ASL) and found that ND had no significant effect on RTs, even though ND has been shown to affect sign recognition (e.g., Caselli, Emmorey, & Cohen-Goldberg, 2021). Sehyr and Emmorey proposed that ND may play a different role in sign recognition than that of sign production.

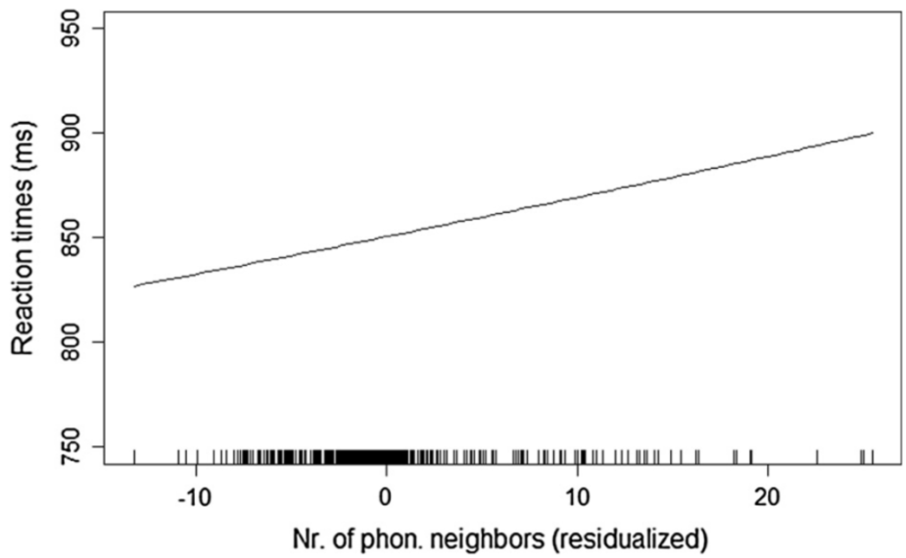


Figure 1: Effect of residualized[1] PhND on naming latencies. Naming latencies increased significantly with the phonological density of a word's neighborhood. From Sadat & colleagues (2014).

In spelling aloud task, Roux & Bonin (2009) found that orthographic ND (OrND) facilitated production – words with a dense neighborhood were spelled quickly and accurately than words with a sparse neighborhood. In aphasic patients, spoken and written spelling tasks showed that neighbors facilitated the successful production of a target word in either modality (Goldrick, Folk, & Rapp, 2010). Tainturier et al. (2013) used a spell-to-dictation task to explore the effect of neighborhood effects on pseudo word spelling. They found that the spelling of pseudo words was impacted by the presence or absence of a close neighbor. This lexical influence increased with the lexical frequency of the target word's neighbors.

To our knowledge, there have been no studies conducted on ND using typed language production as the method of investigation. Therefore, the primary goal of this thesis is to bridge

[1] When a variable in a regression model is residualized, it means that the influence of other variables in the model has been statistically removed from it. This controls for other variables and the residualized variable represents the part of its variation that is not accounted for by the other variables in the model.

the gap in psycholinguistics research and investigate whether the ND findings from other modalities hold in typed production.

Typing architecture

Theories of language production hold that spoken and written production involve broadly similar changes until post-lexical processing. At this stage in written production, graphemes are thought to be maintained in the graphemic buffer, a working memory system used in both reading and spelling (Caramazza & Miceli, 1990; Tainturier & Rapp, 2003). The graphemic buffer keeps the orthographic information (i.e., a sequence of graphemes or abstract letters) active during serial selection of letters (Caramazza et al., 1987). After processing in the graphemic buffer, articulation may occur through different routes: letter-shape conversion (e.g., /bæg/), letter-name conversion (/bi, eɪ, dʒi/), or letter-keystroke conversion, depending on whether the word is being written by hand, spelled aloud, or typed on a keyboard (Bonin et al., 2015).

Given that these architectures are broadly similar at lexical stages and likely differ at post-lexical stages, we use neighbors and ND in this study to gather data about how neighbors affect processing in typing. If processing is similar across speaking and typing, ND should overarchingly inhibit or lengthen naming latencies across our experimental task.

Exploration of sharing the first letter

While the psycholinguistic literature has settled on the notion of neighbors, it's important to note that neighbors are just one way of operationalizing lexical similarity. It is possible that other definitions may also capture – or better capture – the dimensions along which words relate to each other during processing. For example, while neighbors are a binary classification of similarity (words are classed as either neighbors or non-neighbors depending on whether they have a string edit distance of 1 from the target) it is possible to define similarity in a gradient way (e.g., Yarkoni, Balota, and Yap, 2008).

One dimension of similarity that may matter is sharing the first segment with the target. A number of spoken production studies have shown that the number of neighbors that match/mismatch a target's first consonant influences the way it is articulated (Baese-Berk & Goldrick, 2009; Caselli, Caselli, & Cohen-Goldberg, 2016; Goldrick, Vaughn & Murphy, 2013; Yiu & Watson, 2015).

There are fewer studies that have examined the effects of these neighbors on RT. Vitevitch, Armbruster and Chu (2004) found that words with a sparse onset, or a low proportion of neighbors sharing the onset of the target word, were responded to more quickly (and accurately) than words with a dense onset. They used relative onset density - this is the total number of neighbors sharing the first phoneme[2]. However, as mentioned above, Sadat et al. (2014) found no effect of absolute onset density.

There are a few studies that have looked at first letter overlap in written production (Scaltritti, Longcamp, & Alario, 2018b; Roux & Bonin, 2012). Roux and Bonin (2012) reported facilitation in the onset of written production for picture naming when a distractor picture begins with the same letter (regardless of whether the letter represents the same sound). This finding is consistent with cascading activation in written production because the orthographic forms of both the target word and the distractor picture are activated, which in turn strengthens the activation of the constituent graphemes, even though only the target is selected for production.

---

[2] This definition of onset density differs from that used by Sadat et al. (2014). They used an *absolute* onset density, a direct measurement of the number of onset neighbors a given word has. It is an independent value. Vitevitch, Armbruster, & Chu (2004) use *relative* onset density – it is a proportion of the number of onset neighbors for a given word divided by the number of total neighbors the given word has. Absolute onset density was analyzed in this study, and any finding in which ND "shared same first letter" is significant is a representation of that.

This result would not be expected in a serial processing system in which an unselected word would not alter later processing. Scaltritti et al. (2018b) used a continuous word production paradigm task and had participants type their responses. They tested four different types of overlap: word pairs that shared either the first two (SSDD; where 'S' represents a shared letter and 'D' represents a differing letter), the final two (DDSS), or all of their keystrokes (SSSS), and an unrelated baseline condition (DDDD). They found facilitatory effects in the initial overlap condition. These findings are in direct contrast to Sevald & Dell (1994), which had run the same study in speech and found inhibitory effects in the initial overlap condition, potentially due to the changes in processing in each modality.

It is intriguing that the first position of a word has been shown to have overarchingly facilitative priming effects on a target word. Because of these findings, ancillary analyses were run on ND shared first letter. Neighborhood density shared first letter refers to the number of words within a given word's ND that share the same first letter as the target.

However, there is reason to believe that letters function relatively independently of position early on in processing. The next section describes the crux of this thesis in detail: that different definitions of neighborhood can be used to isolate and investigate the mechanisms at work at different stages of processing.

Neighbors and the levels of processing

The traditional definition of the neighbor requires neighbors to differ from the target by no more than 1 segment while requiring all other segments to be in the same linear order. As such, neighbors are similar to the target in both segment identity and order.[3] To our knowledge, the contribution of segment position to lexical similarity has not been considered in any

---

[3] It should be noted that this definition implicitly uses a left-edge (or ordinal) definition of segment position. To our knowledge, studies on neighbors have not explored other definitions of position (e.g., syllabic, both edges, etc.).

neighborhood studies in any modality of production in this way. This question will play a central role in the present work.

Theories of written production generally hold it that at early stages of processing, letter identity is associated with but functionally independent of position.[4] For example, researchers investigating the spelling of dysgraphic patients with damage to the graphemic buffer proposed that orthographic representations consist of multiple tiers including a tier that specifies letter positions and a tier that specifies letter identities (Caramazza & Miceli, 1990; McCloskey et al., 1994; see Figure 2).

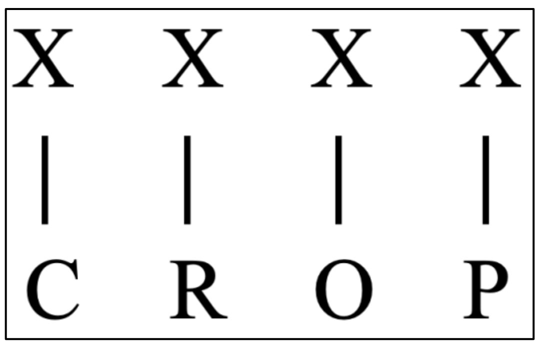


Fig 2. A depiction of the multi-tier hypothesis. Adapted from McCloskey et al. (1994). The letter position tier (denoted by Xs) is the top tier and letter identity tier (denoted by letters) is the bottom tier. The vertical lines show association between tiers that lead to correct letter-to-position mapping.

Many computational theories of spelling also propose that identity is represented independently of position (Glasspool & Houghton, 2005; Houghton, Glasspool & Shallice, 1994; Rumelhart & Norman, 1982), though not all (e.g., Simple Recurrent Networks, Goldberg &

[4] Orthographic representations that are position-dependent have been proposed in other domains such as reading (e.g., open bigrams, Whitney & Grainger, 2004) and elsewhere (Wickelgrams, Rumelhart & McClelland, 1987).

Rapp, 2008). Competitive queuing models, for example, have been used to describe the typing architecture and propose that the order of the keystrokes is determined by the arrangement of activation values, not anything inherent attached to the letter identity (Behmer & Crump, 2017; Rumelhart & Norman, 1982). A recent experimental study provides converging evidence for position-independent orthographic representations. Harrison, Hepner, and Nozari (2020) employed the segmental interference effect using a handwritten picture naming task to test whether letters in one word can activate the same letter in a different word if the letter appears in different positions. They found interference when letters appeared in the same position (e.g., GLOW slowed the production of FLOW) but critically, interference was also found when the letters appeared in different positions (GLOW slowed the production of WOLF). These findings together strongly suggests that letter identity is represented and can function independently of position at certain (likely early) stages of processing.

This fact suggests that words other than traditional neighbors may play a role in written production. Specifically, it opens the possibility that neighbors that share letters but *not* position may become activated.

Consider the word PORK. We can safely assume that PARK would be activated as a neighbor of PORK – as it substitutes the letter “o” for an “a” – but what about CROP? CROP differs from PORK by only one substituted letter. However, unlike PARK, CROP also differs from the target word by not just the *identity* of a single letter, but by the *position* of all of the letters. It is typically assumed that all of the neighbors in a given word’s neighborhood differ from the given word by one letter *in the same position*. This string representation relies on letter identity and position being encoded together during production. However, a *set* neighborhood would only rely on letter identity, not position – neighbors can be anagrammatic, or position-independent. The term comes from the idea that in mathematics, sets focus on identity without encoding order.

The purpose of reviewing these serial order theories is to show that these models do leave room for position-independent letter identity items at some point of processing. We hypothesize that this separation of identity and position would occur only at early stages of processing, and that at later stages of processing, position will play more of a role. To investigate the differences in the relationship between position and letter identity at different stages of processing, we will compare the effects of string and set ND (the total number of a given word's set neighbors) on RT and mean IKI.

Present study

The purpose of this study was to investigate how orthographically similar words become activated during typed production, examining 1) whether or not there are effects of ND on typing and 2) whether different types of neighbors become activated at different stages of processing. We used a standard picture naming task to investigate these questions.

We hypothesized that position-independent neighbors may become active at earlier (e.g., lexical) stages of processing and position-dependent neighbors may become active at later (e.g., post-lexical/articulatory) stages. In order to index earlier vs later processing, this study relied on two different dependent measures: reaction time and mean inter-key interval (IKI). Reaction time is defined as the amount of time that elapses between when the stimulus is first presented and when the first keystroke is registered. At a minimum, visual object recognition, semantic processing, lexical retrieval, and motor planning for the first keystroke must take place during this time. Inter-key intervals are the amount of time that elapses between each keystroke (e.g., from the release of the P key and the depression of the O key when typing PORK). Mean IKI at a minimum indexes processing taking place after the retrieval and articulation of the first letter.

While in theory, RTs could reflect early *and* late processes (e.g., RTs could index motor planning if a participant waits until all the keystrokes have been planned before initiating the first keypress), experimental results suggest that RTs mostly reflect only early (e.g., lexical processing). Specifically, bigram frequency has been shown to influence mean IKIs but not RTs (Gentner et al., 1988; Scaltritti et al., 2016), suggesting that most of a word's letters are not activated at the first keypress (see also Scaltritti, Alario, & Longcamp, 2018a). By contrast, there is some indication that while mean IKIs may primarily index later processing, they may also index earlier processing, likely through cascading activation (e.g., Hameau, 2021).

We considered a number of hypotheses with respect to neighbors at different stages of processing. If position and identity are never functionally separable in typing, we would not see effects of set ND in either RT or mean IKI. If, however, position and identity are functionally independent, then the effects of Set ND would depend on at what stage of processing this independence exists and whether or not lexical processing cascades to later stages. If position-independent neighbors are activated early and activation does not cascade, Set ND should affect RT but not mean IKI. If they are activated early and activation cascade to later stages (or if they are activated at both stages), Set ND should affect both RT and mean IKI. Finally, if they are activated late in processing, Set ND should affect mean IKI only. The same predictions hold true for typically defined (position-dependent) neighbors but with String ND.

Based on the evidence that letter position is relatively independent of position at early stages of processing, we hypothesized that RTs would be influenced by Set ND but not String

ND. In contrast, we hypothesized that only position-dependent neighbors would become activate at later stages, causing String ND but not Set ND to affect mean IKI.

Given the uncertainty of whether or not the first letter overlap is significant in processing, we have examined ND using both the original definitions (in which one letter is different from the target) and a definition where neighbors had to share the first letter as the target (string/set ND shared first letter).

Experiment

Methods

Due to the COVID-19 pandemic, the experiment was initially conducted remotely online. To validate our findings, an in-person laboratory study was also ran when testing capability without masks reopened. The procedures for these two versions were identical (however, see Table 1 for slight differences across both versions of the study).

Participants

Participants (N=76, 52 from the online version and 24 from the offline version) were recruited from the Tufts University for-credit SONA pool. Participants provided informed consent; to be eligible for the study, they additionally needed to consent to having their spoken responses be audio recorded.

Table 1
Differences between online and offline versions of the task

	Online	Offline
Number of participants	52	24
Location	Remote	Tufts University TPLL laboratory in soundproof booth
Software used	PsychoPy, hosted on Pavlovia	PsychoPy

Method of obtaining consent	Clicked button on screen to confirm consent	Signed name on physical consent form
Equipment	Personal computers	iMac desktop, headset with microphone attachment

Materials

The task was created using PsychoPy software (Peirce et al., 2019). The stimuli were simple colored images of everyday items and actions (see Appendix 1 for examples) retrieved from the Internet.

Development of stimuli

The stimulus list was created using the English Lexicon Project – an online lexical database that provides psycholinguistic norms for over 40,000 words (Balota & Yap, 2007) – and were constrained to concrete (picturable), monomorphemic, mono-syllabic words.

The words were also constrained to 1) contain either 3 phonemes and 3 graphemes or 4 phonemes and 4 graphemes and 2) have the same C/V structure in their phonology and orthography. Words with geminates (e.g., EGG) were excluded from the word list. There were 69 CVC words, 70 CVCC words, and 54 CCVC words (e.g., CAT, BALD, and CLAM, respectively) for a total of 193 words. For each word, a computer program identified neighbors by string and set, and ND was calculated as the sum of these neighbors.

In the study design, all of the words were presented to each participant in the form of a simple colored image. In total, 97 typed stimuli were shown to each participant.[5]

[5]We also tested a speech condition of this experiment with half of the prepared stimuli (N=96). Each participant experienced a spoken and typed block. Participants were shown all 193 stimuli divided into these 2 randomly assigned blocks. This testing was done remotely (during the peak COVID-19 pandemic). Data was collected, but issues with data quality and the manually checking each trial for our automated methods of determining RT and duration values are still underway. This thesis focuses primarily on the typed production results.

Procedure

Participants were tasked to complete a picture naming experiment; participants were asked to respond as quickly and as accurately as possible with the names corresponding to pictured objects. Picture naming operationalizes a more natural communication situation in which speakers (or writers, or typists) wish to express an idea verbally. The task therefore uses the same processes involved in conceptually driven word production (Bock & Levelt, 1994; Payne & Tainturier, 2018; Perret & Bonin, 2018). Picture naming is a relatively fast, efficient, and effortless cognitive skill in adults that has provided psycholinguistic research tons of information regarding language processing at different stages of production.

Participants first proceeded through a study block to familiarize themselves with the target name for each picture. Subjects were presented with an image on the left and its corresponding name on the right of the screen and were able to proceed through the study period at their own pace by using the spacebar on their keyboard. After the study period, the experiment began.

This study was originally conceptualized to compare spoken and typed production, with half the images used to collect spoken responses and the other half used to collect typed responses. For each participant, the stimuli were organized into two randomly ordered blocks of 96 (speech) and 97 (typed) items each. In the speech block, participants were instructed to speak their response out loud into their computer microphone. Similarly, in the typed response block, participants typed the name of the stimulus. While both spoken and typed responses were collected, only the typed data were analyzed due to difficulties arising from the pandemic.

Each trial started with a 500 ms fixation cross, followed by a blank screen for 50 ms, which was then followed by the target picture presented at the center of the screen for 1000 ms.

The order of the stimuli was fully randomized across both blocks. The experiment lasted for approximately 30 minutes.

As mentioned above, data were originally collected online while more participants were brought later tested in person to ensure the consistency of results. There were some differences across the online and offline versions of the experimentation. Although they did not significantly impact results, conditions are compared in Table 1.

Results

Data preprocessing

Typing data were obtained from PsychoPy and Pavlovia and combined into a CSV file for the online and offline versions of the experiment. These data were combined within R into a single data frame. Six participants' data were excluded from analyses due to scoring less than 50% accuracy level.

Accuracy analyses were first conducted on all trials using logistic mixed effects models. Subsequently, incorrect trials and trials with RT > ±2.5 SD of participant mean were excluded and RT and mean IKI were analyzed using linear mixed effects models (lmer). For all models, the baseline fixed-effects variables were *trial*, *lexical frequency* (LgSUBTLWF), *concreteness*, *mean bigram frequency*. The values for the latter 3 variables were obtained from the English Lexicon Project (see Appendix B2 for descriptions of the fixed effects) (Balota & Yap, 2007). Different definitions of ND were then added as fixed effects of interest. Each model also included random intercepts for *participant* and *stimulus*. Examples of the models are listed in Table 2.

In all of the analyses, we ultimately compared 3 different definitions of ND: string, set, and ND shared first letter. If a model result was not significant, we also then examined if a definition of ND in which all the neighbors are constrained to share the same length (string/set ND same length) as the target was significant, just to make sure the null result isn't due to a more stringent form of similarity being at work.

Analysis 1: Online versus offline

There were 4130 trials analyzed from the remote version of the experiment, and 2049 observations from the in-lab version. No significant differences were found in any of the measures and across interactions across the online and offline datasets. Therefore, for the remaining analyses, the two datasets were combined and analyzed together.

Table 2
Examples of regression models

Type of model	Model
Accuracy model	total_type_rt_string = glmer(Accuracy ~ TrialInBlock + LgSUBTLWF + Concreteness_Rating + BigramMean + Ortho.String.ND + (1|Participant) + (1|Stimulus), data = total_typedata, family = binomial)
RT model	total_type_rt_string = lmer(RT ~ TrialInBlock + LgSUBTLWF + Concreteness_Rating + BigramMean + Ortho.String.ND + (1|Participant) + (1|Stimulus), data = total_typedata)
Mean IKI model	total_meanIKI_string = lmer(meanIKI ~ TrialInBlock + LgSUBTLWF + Concreteness_Rating + BigramMean + Ortho.String.ND + (1|Participant) + (1|Stimulus), data = total_typedata)

Note: These are just examples of the models run. These models were duplicated for set ND. Regression analyses were run across all data, across only the 3-letter and 4-letter words separately, by participant speed, and by target word frequency. Supplementary analyses can be found in Appendix B.

Analysis 2: Accuracy

There were 6179 trials from 70 participants analyzed for the accuracy models. String ND (z = 1.801, p = .072) did not significantly affect accuracy measures on its own. Upon further analysis, string ND same first letter (z = 2.022, p < .05) and string ND same first letter and same length improved accuracy (z = 2.046, p < .05). Model comparisons showed that neither variable predicted above or beyond the other.

None of the set ND variables on its own (set ND: z = 0.514, p = .607), shared first letter (set ND: z = -0.435, p = .664), same length (set ND: z = 0.722, p = .470), or shared first letter and same length (set ND: z = 0141, p = .888) significantly impacted accuracy.

Analysis 3: Reaction time analyses

There were 4683 trials from 70 participants analyzed for the remaining models. String ND did not have a significant effect on RT (β = 1.006e-02, t = 1.402, p = .163), however, its inhibitory direction does pattern similarly with the results found by Sadat and colleagues (2014). String ND shared first letter and string ND same length also did not significantly effect on RT.

Set ND on its own did not significantly impact RT. However, set ND shared first letter and set ND shared first letter and same length facilitated RT in the typing condition (β = -1.814e-02, t = -2.773, p < .01 and β = -2.339e-02, t = -3.652, p < .001, respectively). As these types of neighbors increased, RT decreased for participants. Set ND shared first letter and same length predicted above and beyond the shared first letter variable on its own.

Analysis 4: Mean IKI analysis

String ND facilitated mean IKI times (β = -2.609e-02, t = -2.818, p < .01); as ND increased, mean IKI times decreased, which meant faster participant responses for a whole word response. Set ND on its own did not significantly affect mean IKI; set ND same length, on the other hand, inhibited mean IKI (β = 1.810e-02, t = 2.078, p < .05) – as set ND increased, the time between keystrokes increased over time.

Post-hoc analysis: Participant speed

In our study, we initially employed regressions to examine the main effects between ND and the time course variables (RT and mean IKI) across all participants. Given the results obtained from Sadat and colleagues (2014) that a strong inhibitory ND effect was found in faster participants, we conducted a post-hoc analysis to investigate potential differences between fast and slow participants. Mean RT across participants was approximately 1600 milliseconds[6]. Fast and slow participant groups were created based on each individual's RT. If their mean RT was less than the average RT across all participants, they were put in the 'fast' category; if their mean RT was greater than the overall average RT, they were put in the 'slow' category. The same models were run across these two new data sets.

Among the fast participants, string ND did not impact RT or mean IKIs. Set ND facilitated RT (β = -2.256e-02, t = -2.581, p <.05) but inhibited (slowed) mean IKI (β = 4.207e-02, t = 2.010, p < .05).

Among slow participants, string ND on its own did not affect RTs, but string ND same length inhibited them (β = 1.535e-02, t = 2.248, p < .05). This finding is reminiscent of Sadat et

[6] This is a slower average reaction time than anticipated. Other typing studies have found RTs closer to 800-1000ms. This larger number is most likely due to the larger sample of our data taken from the online version of our study – the average RT for the offline version was akin to more commonly seen typing latencies.

al. (2014)'s inhibitory findings, however an interaction of speed and string ND yielded insignificant results. Lastly, while set ND on its own did not significantly affect RTs or mean IKIs in slow participants, set ND shared first letter and set ND shared first letter and same length facilitated RT (set first letter: $\beta = -1.713e\text{-}02$, $t = -2.618$, $p < .01$; set first let same length: $\beta = -2.353e\text{-}02$, $t = -3.685$, $p < .001$). There were no significant effects of ND on mean IKIs of slow participants. It seems that first letter and length are important. Although length predicts above and beyond letter after running model comparisons, it seems that letter is the parameter necessary in the significant findings.

These post-hoc findings contribute to a more nuanced understanding of the flexibility and levels of language processing, and further inform our overall conclusions about the presence of position at different stages of processing.

Discussion

This study investigated how neighbors become activated during typed production and tested theories of position-independent representations using novel definitions of ND. A summary of the findings can be found in Table 3. Reaction times were facilitated by Set ND, representing the first demonstration that position-independent neighbors are active during typed production. Interestingly, RT was not influenced by String ND. By contrast, accuracy and mean IKI were both facilitated by String ND and mean IKI was inhibited by Set ND.

Together, these results are consistent with a typed production architecture where early orthographic representations contain letter identities that may be activated independently of position but where activation becomes position-dependent at later stages. As a target word becomes activated at earlier stages, words containing the same letters also become activated (perhaps through spreading activation) even if the letters appear in different positions.

Interestingly, it appears that at this stage neighbors only become active if they have the same first letter as the target. This suggests that although letters are activated independently of position at this stage of processing, the first position plays a crucial role in determining whether or not a neighbor will become active.

At later stages, neighbors appear to become in a more position-dependent manner, as indicated by the effect of String ND on mean IKI. One way this could arise is if letter identity and position come to be represented in a joint manner. For example, if letters were represented as open bigrams (e.g., CAPE: {CA, AP, PE, …}) or Wikelgrams (e.g., CAPE: $_{\#}C_{A}$, $_{C}A_{P}$, $_{A}P_{E}$, $_{P}E_{\#}$) the words they could activate would be likely to contain the same letters in the same positions (e.g., $_{\#}C_{A}$ would more strongly activate CAT than CLAP). It could also occur if letter processing becomes segregated by position.[7]

Table 3

Summary of findings

Analysis 1 - Accuracy	String ND shared first letter and string ND shared first letter & same length *improved accuracy*
Analysis 2 – Reaction time analyses	Set shared first letter ND and set shared first letter & same length *facilitated**
Analysis 3 – Mean IKI	String ND *facilitated* Set ND shared length *inhibited*
Post-hoc analyses – By participant speed	Fast: • set ND *facilitated* RT • set ND *inhibited* mean IKI Slow: • String ND shared length *inhibited*** • Set shared first letter ND and set shared first letter & same length *facilitated**

[7] Although Competitive Queuing is not currently specified in a way to address the processing of non-target words, one way to do so could be to assume that all words simultaneously receive activation from the I and E nodes, just with the target receiving more activation than other words. In this scenario, letters in the same position will become more active across all words than letters in different positions, perhaps allowing the former to play a stronger role in processing than the latter.

Note: 1) N.S. stands for "not significant."
*Length predicted above and beyond first letter, however on its own it did not have a significant effect.
**Interactions run later suggest this finding is inconclusive – however, it is kept in this table of significant findings as it is suggestive of differences between how string and set ND impact processing.

The fact that accuracy is influenced by String ND and not Set ND can be accommodated if we assume that errors primarily involve letter articulation (selecting the right letter at the right time) and thus arise relatively late in processing. If this is the case, it would make sense that position-dependent neighbors and not position-independent neighbors would affect processing.

Can the fact that Set ND affects mean IKIs be explained in this architecture given that position-independent neighbors are proposed to only be activated at earlier stages? While not directly predicted by the proposal that early and late representations are position-independent and position-dependent, respectively, it is possible within an architecture where earlier processing can cascade to later processes. In this scenario, set neighbors become activated at earlier stages of processing and activation from these words cascades to later processes, ultimately affecting IKIs.

Let's now turn to the direction of the effects. The experiment found that set and string neighbors uniformly facilitate processing, with the exception that set neighbors inhibited mean IKIs. At a basic level, these results suggest that typing is facilitated by co-activated segments and that any conflicting representations (i.e., non-target segments and lexical items) either don't slow processing or if they do, their effects are outweighed by the facilitative effects of segmental overlap. The finding that set ND inhibits mean IKIs makes sense from the perspective that at late stages, position-specific representations matter. Since position-independent neighbors are most likely to have letters in the wrong position, they would likely provide activation that conflicts with the articulation of the target.

Differences in string ND findings in the literature

In our study, string ND inhibited RT in only slow participants (not conclusively) and facilitated mean IKI for all participants. Although Sadat et al. (2014) provided convincing evidence that the traditional definition of ND inhibits naming latencies, research on ND has shown inconsistent findings (Gordon & Kurczek, 2013; Hameau et al., 2021). This could be due to multiple reasons, e.g., confounding variables, activation levels, task demands, atypical samples.

Sadat and colleagues (2014) suggested that a reason some studies yield contradicting results could be because researchers must control for confounding variables with finer-grained analyses. This was seen in their re-analyses of studies that eventually led to either A) no longer seeing the original significant facilitative effect or B) completely reversing the significant pattern. Perhaps finer-grained analyses of this study could yield similar results.

Chen and Mirman (2012) proposed that neighbors can induce facilitation or inhibition depending on how strongly activated they are. Only ‘strongly’ active neighbors exert a net inhibitory effect, and ‘weakly’ active neighbors exert a net facilitative effect. They argue that word production is a more semantically driven task, therefore phonological neighbors would be more strongly activated in word recognition tasks instead.

Across many ND studies, an interesting pattern can be seen: Given a particular task and neighbor type, the effects are quite consistent but the direction of the effect – facilitation vs inhibition – differs across tasks and neighbor types (Chen & Mirman, 2012). Bonin and colleagues (2015) stated that different tasks use different cognitive pathways – therefore it would make sense that paradigms involving outright production of target words and their neighbors would yield different results as paradigms that only require articulation of a target word.

Differences can also be seen across different samples. Gordon & Kurczek (2013) found ND inhibited production in older adults but was insignificant in younger adult production. Aphasic speakers have shown facilitatory effects of ND on spoken production (Goldrick, Folk, & Rapp, 2010). Lastly, dysgraphic patients and patients with graphemic buffer deficit have shown improved spelling that generalized to untrained words that shared orthography with the trained words (Kohnen, Nickels, Coltheart, & Brunsdon, 2008; Raymer, Cudworth & Haley, 2003)

These studies leave open questions about the conditions under which ND facilitation or inhibition is exerted, and the role of related lexical characteristics.

Flexibility of planning

The post-hoc speech analyses were run because Sadat and colleagues (2014) found a strong inhibitory effect of ND in faster participants, and that this effect increases with increasing RT of the participants. Previous research suggests that a participant's speech rate can have cascading effects on multiple linguistic processes. Research has shown that phonological processes change (e.g., consonant cluster reduction, consonant assimilation, etc.) depending on speech rate. In addition, differences in speech rate may lead to differences in word retrieval speed, which directly impacts RT and mean IKIs.

String ND same length inhibited slow participants RTs – as string ND of the target word increased, slow participants took longer to respond to the stimuli. This finding is intriguing and mimics that of Sadat et el. (2018) but yielded an insignificant interaction which may discount its effect. The pattern could make sense – if string neighbors are activated by feedback, and feedback takes time to register, perhaps this is why we only see these inhibitory string ND findings in slow participant data. Position-specific neighbors may be activated by the time the slow participants execute the first keystroke.

Set ND, on the other hand, facilitated fast and slow participants RTs, and inhibited fast mean IKIs. The facilitation results are in line with what was previously mentioned – early stages of processing do not require position-specific neighbors to help prime target word production. Set ND may inhibit mean IKIs at overarchingly and specifically in the fast participants (though it is possible that the fast participants are 'carrying' the overall effect) because by this later point of processing, when articulation has already begun, letter position is crucial to facilitating production.

Significant findings of similar length and first letter

Model comparison showed that neighbors sharing the same length (set ND shared length) predicted beyond shared first letter in impacting RTs. Same length clearly increases the fit or influence of ND on RTs and mean IKIs. This in and of itself could suggest that lexical selection is guided by representations that are not position specific. Alternatively, this could be explained by Houghton's (2018) serial order graded both-edges scheme. Consider the question broached by Fischer-Baum (2018) to describe this model:

"Which letter in the word CANDY is in the same position as the E in NEST? …for different schemes, the E in NEST could be described as the second letter or the letter after the N. If the E is the second letter in the word NEST, then the A in CANDY is in the same position as the E in NEST. If the E is the letter after the N in the word NEST, then the D in CANDY is in the same position as the E in NEST."

Our orthographic findings align with this model of serial order in which the same length is necessary for two words or sequences to mimic similar coordinate positions. It seems only when a target and its neighbors share the same length can its ND facilitate production – only when the target and neighbor letter positions match can this effect occur. This graded both-edges scheme has been used to code position for both linguistic and non-linguistic sequences, which makes it an intriguing model that can help situate language processing in the larger cognitive system (Fischer-Baum, 2018). To further investigate this, error analyses akin to those mentioned in Fischer-Baum (2018) can be used to isolate preservation effects across words and position boundaries.

Despite the impact of length on the models, shared first letter is still critical to most of the significant findings of this study. It is interesting that even though set ND is inherently position-independent, set ND same first letter facilitated RT. This could support the competitive queuing model of serial order, if the model allows for non-zero deactivation of letter items that could then in turn prime subsequent words (Scaltritti et al., 2018b). Alternatively, perhaps there is some aspect of position that we did not account for in our paradigm that allows both the position-dependent and position-independent variables to coexist and dually impact production. Future research should strive to identify (or generate) a serial order mechanism that can account for these findings.

Limitations and future research

Testing for this experiment was completed for the most part during the peak of the COVID-19 pandemic. Because of this, less than half of the trials were completed in lab (the majority were done remotely, on the participants' own laptop computer. This limited our ability to check for quality control mid-experiment, like we would be able to do in lab. In addition, participants only saw half of the stimuli in the typing block; the other half was in the speech block not discussed in this paper. This within-subjects designed limited the stimuli per conditional block.

Despite these limitations, this study provides plenty of avenues for future research. Firstly, a replication should be conducted to ensure that none of the limitations or any other confounding variables led to our results. These analyses should be tested in other modalities (e.g., speech, sign) to determine the generalizability of the findings and to potentially bring us one step closer to a comprehensive serial order mechanism that can account for the position-independent effects we found.

Conclusion

It is generally assumed that when a word is activated in the lexicon, its neighbors are also activated and impact the target word's production. This thesis introduced the novel idea that there may be different types of neighbors at different stages of processing and found evidence to suggest position only matters at later stages of processing. Future research should continue investigating the role of position and identity on the stages of language production.

Bibliography

Arnold, H. S., Conture, E. G., & Ohde, R. N. (2005). Phonological neighborhood density in the picture naming of young children who stutter: Preliminary study. Journal of Fluency Disorders, 30(2), 125–148.

Baese-Berk, M., & Goldrick, M. (2009). Mechanisms of interaction in speech production. *Language and cognitive processes*, *24*(4), 527-554.

Balota, D. & Yap, M. (2007). The English Lexicon Project. *Behavior Research Methods*, *39*(3), 445-459.

Baus, C., Costa, A., & Carreiras, M. (2008). Neighbourhood density and frequency effects in speech production: A case for interactivity. Language and Cognitive Processes, 23(6), 866–888.

Behmer, L. P., Jr., & Crump, M. J. C. (2017). The dynamic range of response set activation during action sequencing. *Journal of Experimental Psychology: Human Perception and Performance, 43*, 537–554.

Bock, K., & Levelt, W. (1994). Grammatical encoding. In M.A. Gernsbacher (Ed.), Handbook of psycholinguistics, pp. 945–984. San Diego, CA: Academic Press.

Bonin, P., Méot, A., & Bugaiska, A. (2018). Concreteness norms for 1,659 French words: Relationships with other psycholinguistic variables and word recognition times. *Behavior research methods*, *50*, 2366-2387.

Bonin, P., Méot, A., Lagarrigue, A., & Roux, S. (2015). Written object naming, spelling to dictation, and immediate copying: Different tasks, different pathways? Quarterly Journal of Experimental Psychology, 68(7), 1268-1294.

Brysbaert, M., & New, B. (2009). Moving beyond Kučera and Francis: A critical evaluation of current word frequency norms and the introduction of a new and improved word frequency measure for American English. *Behavior research methods*, *41*(4), 977-990.

Brysbaert, M., Van Wijnendaele, I., & De Deyne, S. (2000). Age-of-acquisition effects in semantic processing tasks. *Acta psychologica*, *104*(2), 215-226.

Caramazza, A., & Miceli, G. (1990). The structure of graphemic representations. *Cognition*, *37*(3), 243-297.

Caramazza, A., Miceli, G., Villa, G., & Romani, C. (1987). The role of the Graphemic Buffer in spelling: Evidence from a case of acquired dysgraphia. *Cognition. 26*: 59–85.

Caselli, N. K., Caselli, M. K., & Cohen-Goldberg, A. M. (2016). Inflected words in production: Evidence for a morphologically rich lexicon. *Quarterly Journal of Experimental Psychology*, *69*(3), 432-454.

Caselli, N. K., Emmorey, K., & Cohen-Goldberg, A. M. (2021). The signed mental lexicon: Effects of phonological neighborhood density, iconicity, and childhood language experience. *Journal of Memory and Language*, *121*, 104282.

Chen, Q. & Mirman, D. (2012). Competition and cooperation among similar representations: Toward a unified account of facilitative and inhibitory effects of lexical neighbors. *Psychological Review, 119*(2), 417-430.

Coltheart M, Davelaar E, Jonasson JE, Besner D. Access to the internal lexicon. In: Dornio S, editor. *Attention and performance.* VI. Hillsdale, NJ: Erlbaum; 1977. pp. 535–555.

Dell, G. S. (1986). A spreading-activation theory of retrieval in sentence production. *Psychological Review, 93,* 283–321.

Fischer-Baum, S. (2018). A common representation of serial position in language and memory. In *Psychology of learning and motivation* (Vol. 68, pp. 31-54). Academic Press.

Gentner, D. R., Larochelle, S., & Grudin, J. (1988). Lexical, Sublexical, and peripheral effects in skilled typewriting. *Cognitive Psychology*, *548,* 524–548.

Glasspool, D. W., & Houghton, G. (2005). Serial order and consonant–vowel structure in a graphemic output buffer model. *Brain and language*, *94*(3), 304-330.

Goldberg, A. M., & Rapp, B. (2008). Is compound chaining the serial-order mechanism of spelling? A simple recurrent network investigation. *Cognitive Neuropsychology*, *25*(2), 218-255.

Goldrick, M., Folk, J. R., & Rapp, B. (2010). Mrs. Malaprop's neighborhood: Using word errors to reveal neighborhood structure. *Journal of Memory and Language*, *62*(2), 113-134.

Goldrick, M., Vaughn, C., & Murphy, A. (2013). The effects of lexical neighbors on stop consonant articulation. *journal of the Acoustical Society of America*, *134*(2), EL172-EL177. https://doi.org/10.1121/1.4812821

Gordon, J. K., & Kurczek, J. (2013). The aging neighborhood: Phonological density in naming. Language and Cognitive Processes.

Grainger, J., & Whitney, C. (2004). Does the huamn mnid raed wrods as a wlohe?. *Trends in cognitive sciences*, *8*(2), 58-59.

Hameau, S., Biedermann, B., Robidoux, S., & Nickels, L. (2021). Effects of phonological neighbourhood density and frequency in picture naming. *Journal of Memory and Language*, *120*, 104248.

Harrison, W., Hepner, C., & Nozari, N. (2020). Is Segmental Interference Position-dependent?. In *CogSci*.

Houghton, G. (2018). Action and perception in literacy: A common-code for spelling and reading. *Psychological Review*, *125*(1), 83.

Houghton, G., Glasspool, D. W., & Shallice, T. (1994). Spelling and serial recall: Insights from a competitive queueing model. In *Handbook of spelling: Theory, process, and intervention*. Wiley.

Kandel, S., Peereman, R., Grosjacques, G., & Fayol, M. (2011). For a psycholinguistic model of handwriting production: Testing the syllable-bigram controversy. *Journal of Experimental Psychology: Human Perception and Performance, 37*(4), 1310–1322. https://doi.org/10.1037/a0023094

Kohnen, S., Nickels, L., Coltheart, M., & Brunsdon, R. (2008). Predicting generalization in the training of irregular-word spelling: Treating lexical spelling deficits in a child. *Cognitive neuropsychology*, *25*(3), 343-375.

Levelt, W. J. M., Roelofs, A., & Meyer, A. S. (1999). A theory of lexical access in speech production. *Behavioral and Brain Sciences, 22*(1), 1-38.

McClelland, J. L. (1993). Toward a theory of information processing in graded, random, and interactive networks. In D. E. Meyer & S. Kornblum (Eds.), *Attention & Performance*

XIV: Synergies in experimental psychology, artificial intelligence and cognitive neuroscience, 655– 688. Cambridge, MA: MIT Press.

McCloskey, M., Badecker, W., Goodman-Schulman, R. A., & Aliminosa, D. (1994). The structure of graphemic representations in spelling: Evidence from a case of acquired dysgraphia. *Cognitive Neuropsychology*, *11*(3), 341-392.

Pavlovia. Available online: https://pavlovia.org/.

Payne, J. S., & Tainturier, M. J. (2018). tDCS Facilitation of Picture Naming: Item-specific, task general, or neither?. *Frontiers in neuroscience*, *12*, 549.

Peirce, J. W., Gray, J. R., Simpson, S., MacAskill, M. R., Höchenberger, R., Sogo, H., Kastman, E., Lindeløv, J. (2019). PsychoPy2: experiments in behavior made easy. *Behavior Research Methods.* 10.3758/s13428-018-01193-y

Pérez, M. Á. (2007). Age of acquisition persists as the main factor in picture naming when cumulative word frequency and frequency trajectory are controlled. The Quarterly Journal of Experimental Psychology, 60(1), 32–42.

Perret, C., & Bonin, P. (2019). Which variables should be controlled for to investigate picture naming in adults? A Bayesian meta-analysis. *Behavior research methods*, *51*(6), 2533-2545.

Raymer, A., Cudworth, C., & Haley, M. (2003). Spelling treatment for an individual with dysgraphia: Analysis of generalisation to untrained words. *Aphasiology*, *17*(6-7), 607-624.

Roux, S., & Bonin, P. (2009). Neighborhood effects in spelling in adults. *Psychonomic Bulletin & Review*, *16*, 369-373.

Roux, S., & Bonin, P. (2012). Cascaded processing in written naming: Evidence from the picture–picture interference paradigm. *Language and Cognitive Processes*, *27*(5), 734-769.

Rumelhart, D. E., McClelland, J. L., & the Parallel Distributed Processing Research Group. (1986). *Parallel distributed processing: Explorations in the microstructure of cognition.* Cambridge, MA: MIT Press.

Rumelhart, D. E., & McClelland, J. L. (1987). Learning the past tenses of English verbs: Implicit rules or parallel distributed processing? In B. MacWhinney (Ed.), Mechanisms of language acquisition (pp. 195–248). Hillsdale, NJ: Lawrence Erlbaum

Rumelhart, D. E., & Norman, D. A. (1982). Simulating a skilled typist: A study of skilled cognitive-motor performance. *Cognitive science*, *6*(1), 1-36.

Sadat, J., Martin, C. D., Costa, A., & Alario, F. X. (2014). Reconciling phonological neighborhood effects in speech production through single trial analysis. *Cognitive Psychology, 68,* 33–58.

Scaltritti, M., Arfe, B., Torrance, M., & Peressotti, F. (2016). Typing pictures: Linguistic processing cascades into finger movements. *Cognition*, *156*, 16-29.

Scaltritti, M., Alario, F.X., & Longcamp, M. (2018a). The scope of planning serial actions during typing. *Journal of Cognitive Neuroscience 30*(11), 1620–1629.

Scaltritti, M., Longcamp, M., & Alario, F.X. (2018b).The serial order of response units in word production: The case of typing. *Journal of Experimental Psychology: Learning, Memory, and Cognition*, *44*(5), 819-825.

Sehyr, Z. S., & Emmorey, K. (2022). The effects of multiple linguistic variables on picture naming in American Sign Language. *Behavior Research Methods*, *54*(5), 2502-2521.

Snyder, K.M. & Logan, G.D. (2014) The problem of serial order in skilled typing. *Journal of Experimental Psychology: Human Perception and Performance*, *40*(4), 1697-1717.

Tainturier, M. J., Bosse, M. L., Roberts, D. J., Valdois, S., & Rapp, B. (2013). Lexical neighborhood effects in pseudoword spelling. *Frontiers in psychology*, *4*, 862.

Tainturier, M. J., & Rapp, B. (2003). Is a single graphemic buffer used in reading and spelling?. *Aphasiology*, *17*(6-7), 537-562.

Vitevitch, M. S., & Stamer, M. K. (2009). The influence of neighborhood density (and neighborhood frequency) in Spanish speech production: A follow-up report (Vol. 1),. University of Kansas, Spoken Language Laboratory Technical Report (pp. 1-6).

Vitevitch, M. S., Armbruster, J., & Chu, S. (2004). Sublexical and lexical representations in speech production: Effects of phonotactic probability and onset density. Journal of Experimental Psychology. Learning, Memory, and Cognition, 30(2), 514–529.

Yarkoni, T., Balota, D., & Yap, M. (2008). Moving beyond Coltheart's N: A new measure of orthographic similarity. *Psychonomic bulletin & review*, *15*(5), 971-979.

Yiu, L. K., & Watson, D. G. (2015). When overlap leads to competition: Effects of phonological encoding on word duration. *Psychonomic bulletin & review*, *22*, 1701-1708.

Appendices

Appendix A. Results and graphs of findings

A1. Accuracy

Table A1.1. Accuracy analyses for string and set ND

	Dependent variable:	
	Accuracy	
	(1)	(2)
TrialInBlock	0.022	0.021
	(0.036)	(0.036)
LgSUBTLWF	0.564***	0.610***
	(0.106)	(0.104)
Concreteness_Rating	0.505***	0.530***
	(0.099)	(0.100)
BigramMean	-0.135	-0.078
	(0.108)	(0.105)
Ortho.String.ND	0.201	
	(0.111)	
Ortho.Set.ND		0.054
		(0.106)
Constant	1.666***	1.668***
	(0.135)	(0.135)
Observations	6,114	6,114
Log Likelihood	-2,676.088	-2,677.555
Akaike Inf. Crit.	5,368.177	5,371.110
Bayesian Inf. Crit.	5,421.923	5,424.856
Note:	*p<0.05; **p<0.01,***p<0.001	

Table A1.2. Accuracy analyses for string ND shared first letter and string ND shared first letter & same length

	Dependent variable:	
	Accuracy	
	(1)	(2)
TrialInBlock	0.021	0.021
	(0.036)	(0.036)
LgSUBTLWF	0.578***	0.588***
	(0.104)	(0.103)
Concreteness_Rating	0.517***	0.512***
	(0.099)	(0.098)
BigramMean	-0.153	-0.124
	(0.109)	(0.104)
Ortho.String.ND..Same.1st.Let.	0.223*	
	(0.110)	
Ortho.String.ND..Same.1st.Let..SameLength		0.212**
		(0.104)
Constant	1.665***	1.665***
	(0.135)	(0.134)
Observations	6,114	6,114
Log Likelihood	-2,675.677	-2,675.636
Akaike Inf. Crit.	5,367.354	5,367.271
Bayesian Inf. Crit.	5,421.101	5,421.018
Note:	*p<0.05; **p<0.01, ***p<0.001	

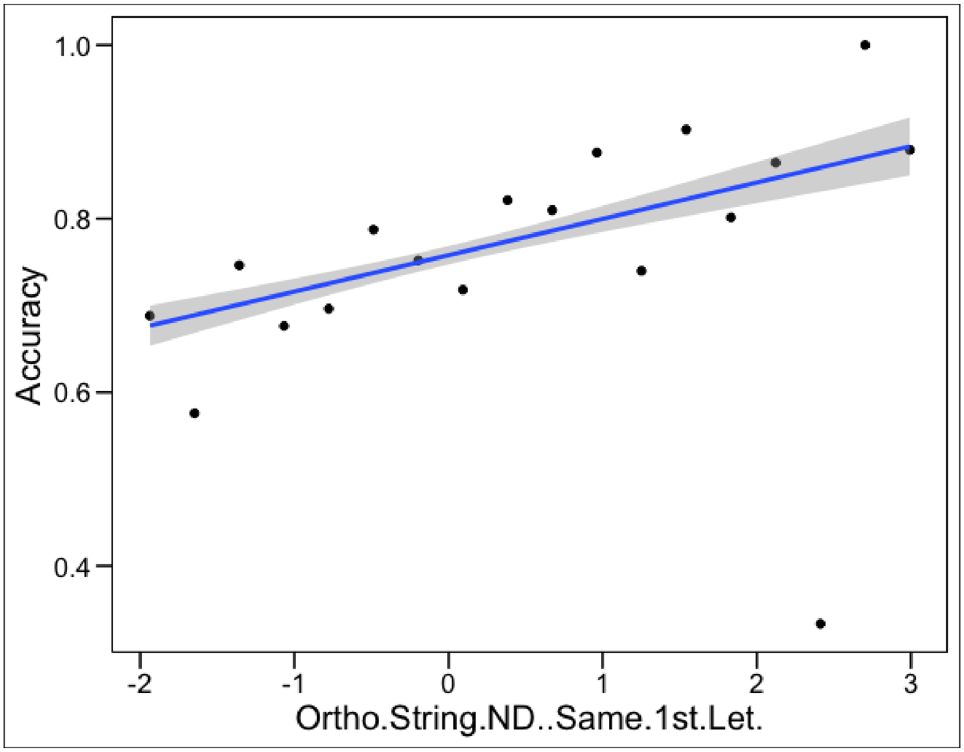


Fig 1. String ND shared first letter improved accuracy

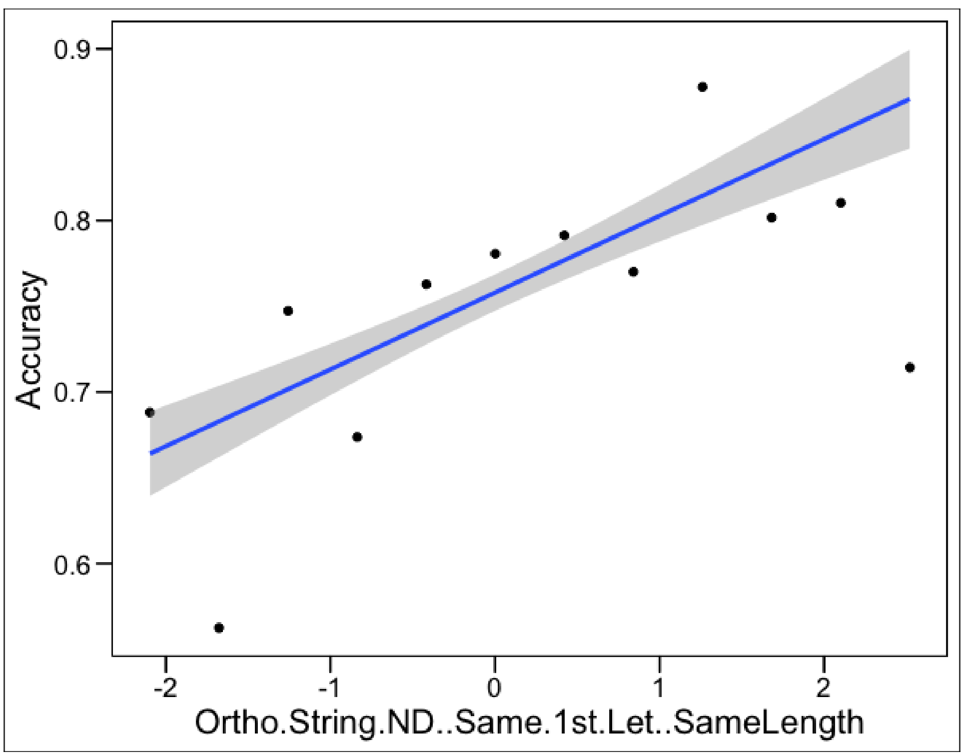


Fig 2. String ND shared first letter & same length improved accuracy

A2. RT

Table A2.1. RT analyses for string and set ND

	Dependent variable:	
	RT	
	(1)	(2)
TrialInBlock	0.001	0.001
	(0.003)	(0.003)
LgSUBTLWF	-0.033***	-0.031***
	(0.007)	(0.007)
Concreteness_Rating	-0.026***	-0.026***
	(0.006)	(0.006)
BigramMean	-0.008	-0.001
	(0.007)	(0.007)
Ortho.String.ND	0.010	
	(0.007)	
Ortho.Set.ND		-0.012*
		(0.007)
Constant	0.470***	0.470***
	(0.024)	(0.024)
Observations	4,652	4,652
Log Likelihood	1,124.197	1,124.885
Akaike Inf. Crit.	-2,230.393	-2,231.769
Bayesian Inf. Crit.	-2,172.388	-2,173.764
Note:	*p<0.05; **p<0.01,***p<0.001	

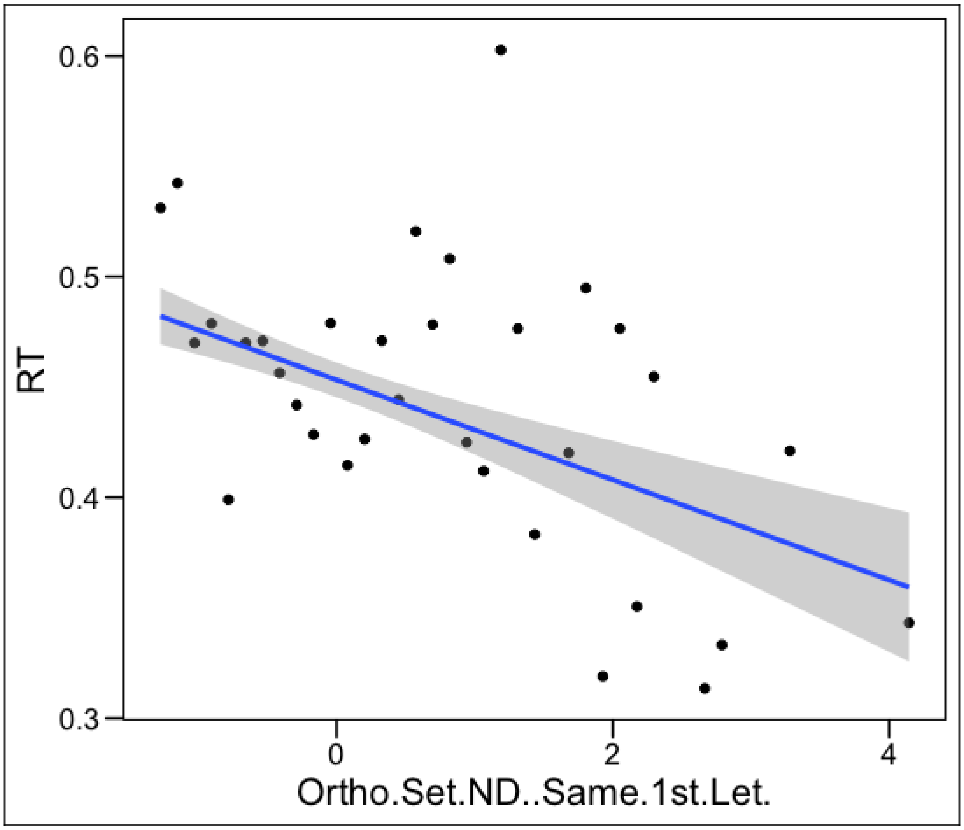


Fig 3. Set ND shared first letter decreased RT

Table A2.2. RT analyses for set ND shared first letter & same length

	Dependent variable:
	RT
TrialInBlock	0.001
	(0.003)
LgSUBTLWF	-0.034***
	(0.006)
Concreteness_Rating	-0.029***
	(0.006)
BigramMean	-0.001
	(0.006)
Ortho.Set.ND..Same.1st.Let..SameLength	-0.023***
	(0.006)
Constant	0.470***
	(0.024)
Observations	4,652
Log Likelihood	1,129.562
Akaike Inf. Crit.	-2,241.124
Bayesian Inf. Crit.	-2,183.119
Note:	*p<0.05; **p<0.01,***p<0.001

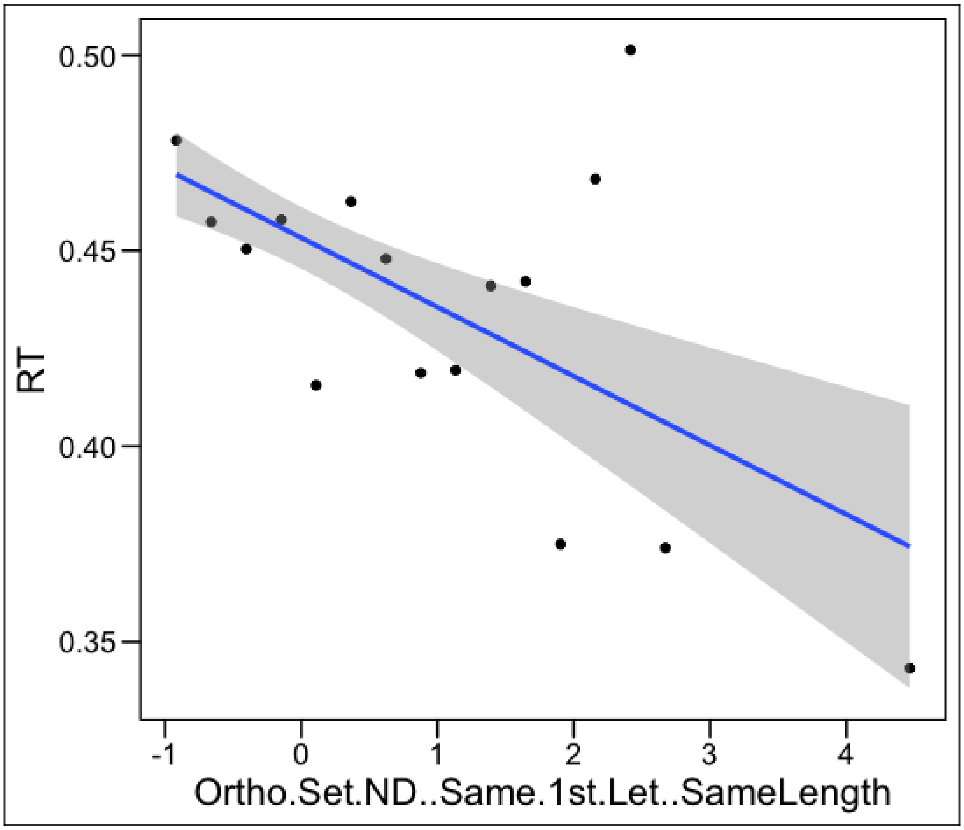


Fig 4. Set ND shared first letter & same length decreased RT

A3. Mean IKI

Table A3.1. Mean IKI analyses for string and set ND

	Dependent variable:	
	meanIKI	
	(1)	(2)
TrialInBlock	-0.019***	-0.018***
	(0.004)	(0.004)
LgSUBTLWF	-0.017*	-0.021**
	(0.009)	(0.009)
Concreteness_Rating	-0.008	-0.009
	(0.008)	(0.008)
BigramMean	-0.018**	-0.031***
	(0.009)	(0.009)
Ortho.String.ND	-0.026***	
	(0.009)	
Ortho.Set.ND		0.016*
		(0.009)
Constant	-1.646***	-1.645***
	(0.032)	(0.032)
Observations	4,652	4,652
Log Likelihood	-717.049	-719.361
Akaike Inf. Crit.	1,452.099	1,456.722
Bayesian Inf. Crit.	1,510.104	1,514.728
Note:	*p<0.05; **p<0.01, ***p<0.001	

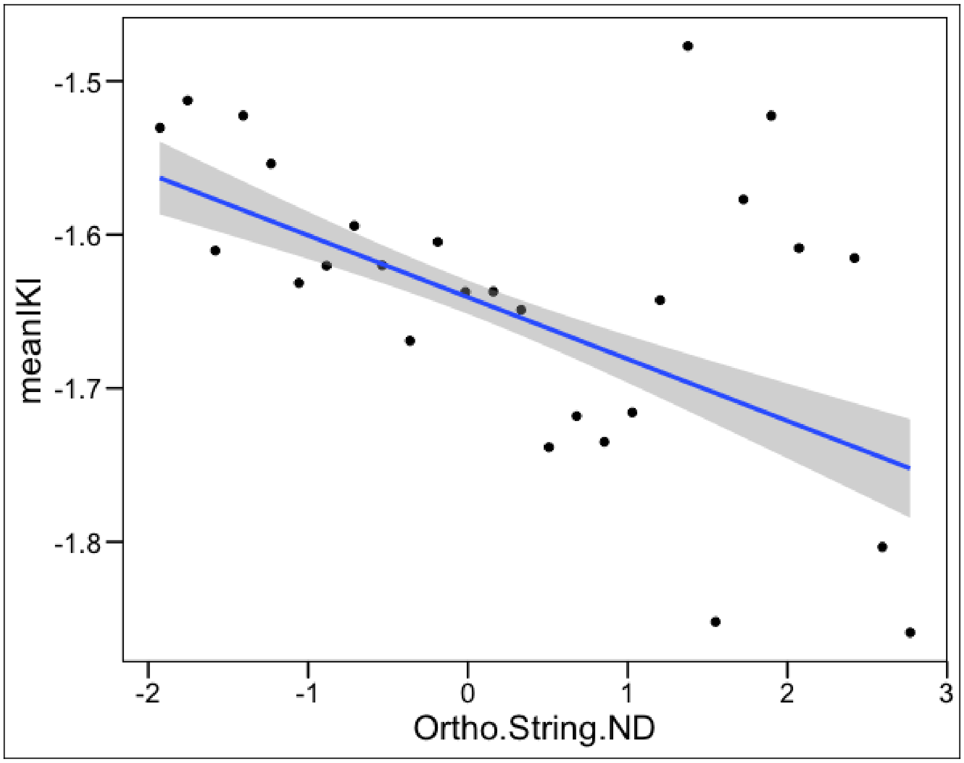


Fig 5. String ND led to shorter mean IKIs

Table A3.2. Mean IKI analyses for set ND same length

	Dependent variable:
	meanIKI
TrialInBlock	-0.018^{***}
	(0.004)
LgSUBTLWF	-0.020^{**}
	(0.009)
Concreteness_Rating	-0.008
	(0.008)
BigramMean	-0.030^{***}
	(0.009)
Ortho.Set.ND.SameLength	0.018^{**}
	(0.009)
Constant	-1.645^{***}
	(0.032)
Observations	4,652
Log Likelihood	-718.873
Akaike Inf. Crit.	1,455.747
Bayesian Inf. Crit.	1,513.752
Note:	$^{*}p<0.05$; $^{**}p<0.01$, $^{***}p<0.001$

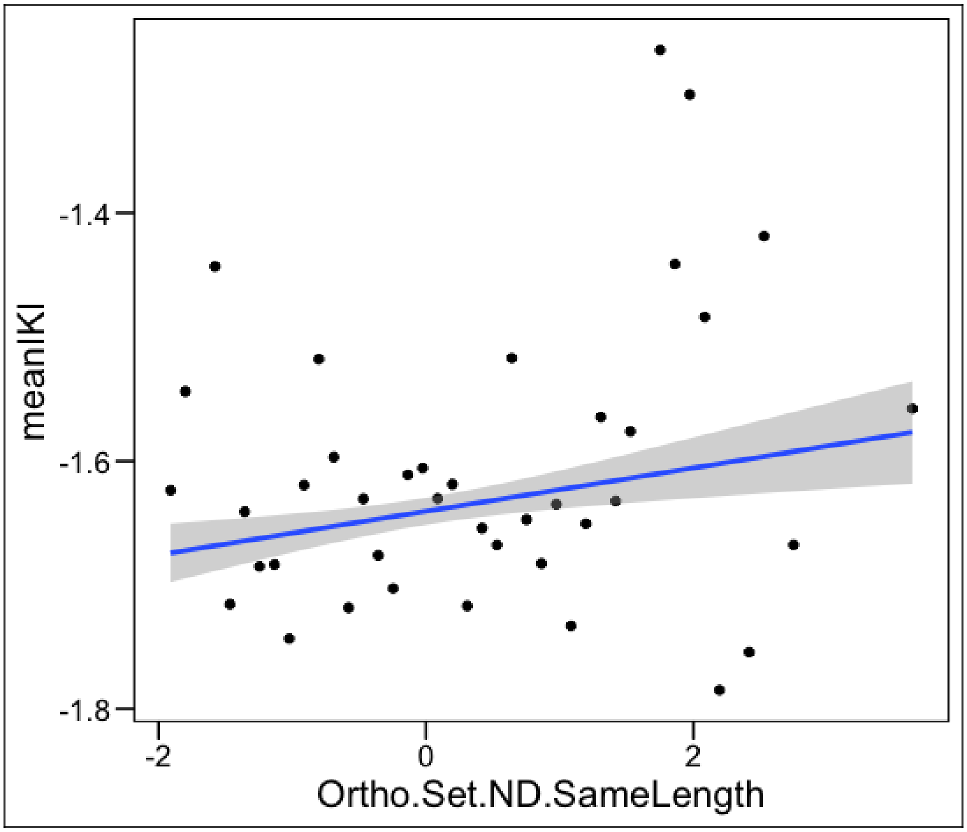


Fig 6. Set ND same length led to longer mean IKI

A4. Participant speed

Table A4.1. Fast RT analyses string & set ND

	Dependent variable:	
	RT	
	(1)	(2)
TrialInBlock	-0.009*	-0.009*
	(0.005)	(0.005)
LgSUBTLWF	-0.039***	-0.039***
	(0.009)	(0.009)
Concreteness_Rating	-0.039***	-0.039***
	(0.009)	(0.008)
BigramMean	-0.006	0.002
	(0.009)	(0.009)
Ortho.String.ND	0.007	
	(0.010)	
Ortho.Set.ND		-0.023***
		(0.009)
Constant	0.216***	0.215***
	(0.037)	(0.037)
Observations	1,335	1,335
Log Likelihood	212.738	215.628
Akaike Inf. Crit.	-407.475	-413.256
Bayesian Inf. Crit.	-360.705	-366.486
Note:	*p<0.05; **p<0.01, ***p<0.001	

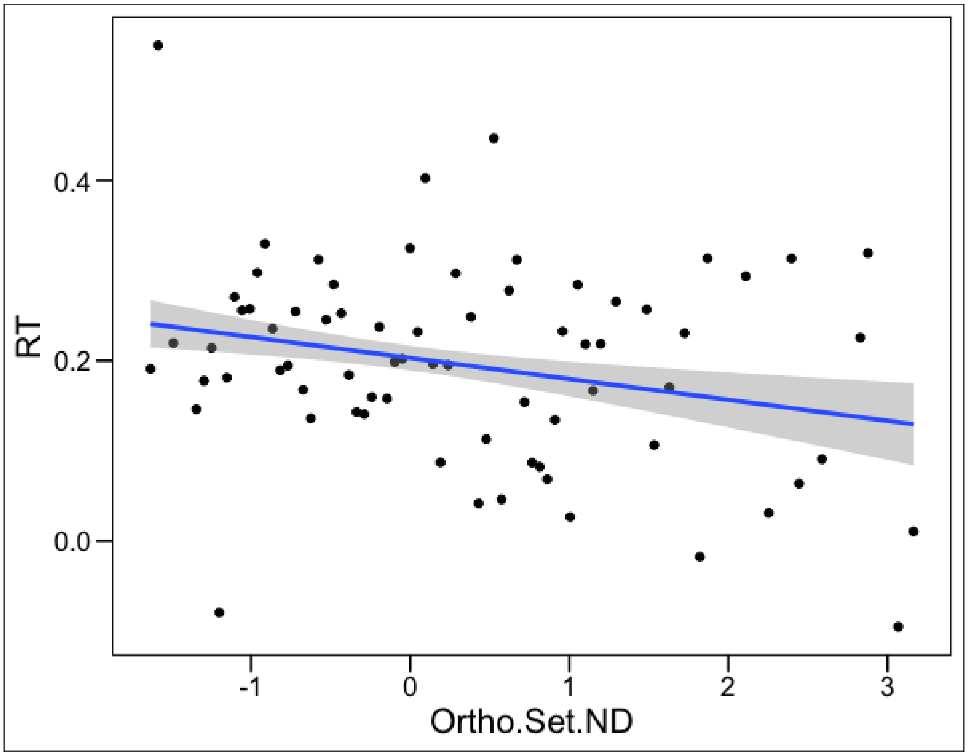


Fig 7. Set ND decreased RT in *fast* participants

Table A4.2. Fast mean IKI analyses string & set ND

	Dependent variable:	
	meanIKI	
	(1)	(2)
TrialInBlock	-0.009***	-0.009***
	(0.001)	(0.001)
LgSUBTLWF	-0.002	-0.003
	(0.002)	(0.002)
Concreteness_Rating	-0.00002	-0.0004
	(0.002)	(0.002)
BigramMean	-0.004**	-0.007***
	(0.002)	(0.002)
Ortho.String.ND	-0.006***	
	(0.002)	
Ortho.Set.ND		0.004**
		(0.002)
Constant	0.187***	0.187***
	(0.010)	(0.010)
Observations	1,335	1,335
Log Likelihood	2,027.948	2,026.606
Akaike Inf. Crit.	-4,037.896	-4,035.213
Bayesian Inf. Crit.	-3,991.125	-3,988.443
Note:	*p<0.05; **p<0.01,***p<0.001	

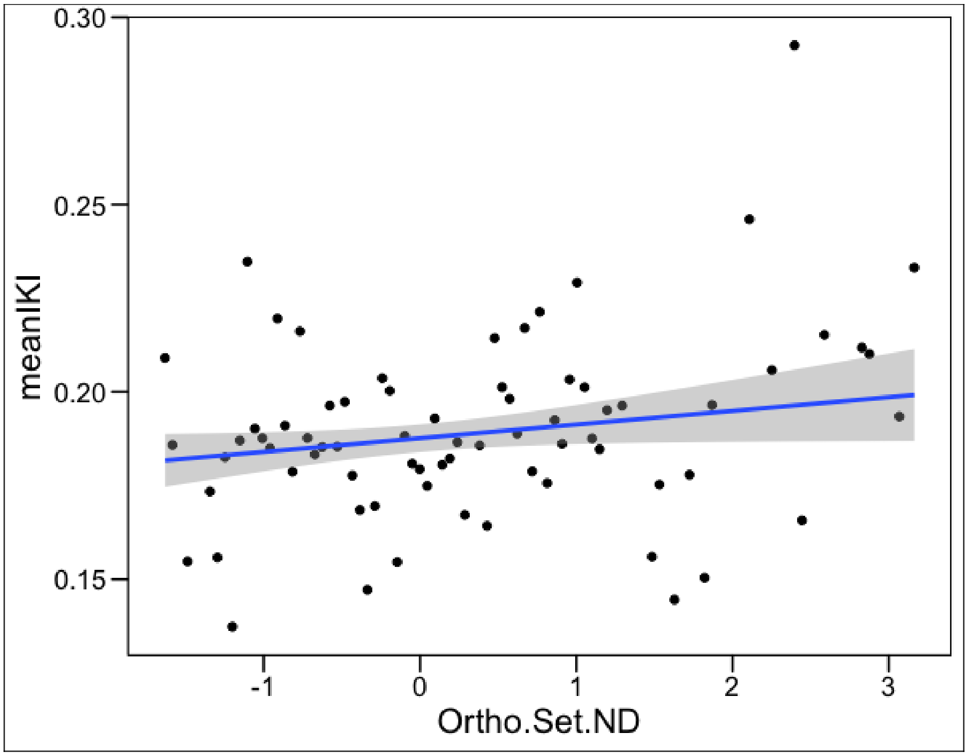


Fig 8. Set ND increased mean IKI in *fast* participants

Table A4.3. Slow RT analyses string & set ND

	Dependent variable:	
	RT	
	(1)	(2)
TrialInBlock	0.005	0.005
	(0.003)	(0.003)
LgSUBTLWF	-0.030***	-0.028***
	(0.007)	(0.007)
Concreteness_Rating	-0.019***	-0.019***
	(0.006)	(0.006)
BigramMean	-0.009	-0.003
	(0.007)	(0.007)
Ortho.String.ND	0.012*	
	(0.007)	
Ortho.Set.ND		-0.009
		(0.007)
Constant	0.563***	0.562***
	(0.015)	(0.015)
Observations	3,317	3,317
Log Likelihood	892.804	892.302
Akaike Inf. Crit.	-1,767.608	-1,766.603
Bayesian Inf. Crit.	-1,712.646	-1,711.642
Note:	*p<0.05; **p<0.01,***p<0.001	

Table A4.4. Slow mean IKI analyses string & set ND

	Dependent variable:	
	meanIKI	
	(1)	(2)
TrialInBlock	-0.002	-0.002
	(0.001)	(0.001)
LgSUBTLWF	-0.003	-0.004*
	(0.002)	(0.002)
Concreteness_Rating	-0.001	-0.001
	(0.002)	(0.002)
BigramMean	-0.003	-0.004**
	(0.002)	(0.002)
Ortho.String.ND	-0.003	
	(0.002)	
Ortho.Set.ND		0.002
		(0.002)
Constant	0.216***	0.216***
	(0.008)	(0.008)
Observations	3,317	3,317
Log Likelihood	4,167.762	4,166.857
Akaike Inf. Crit.	-8,317.524	-8,315.715
Bayesian Inf. Crit.	-8,262.563	-8,260.754
Note:	*p<0.05; **p<0.01,***p<0.001	

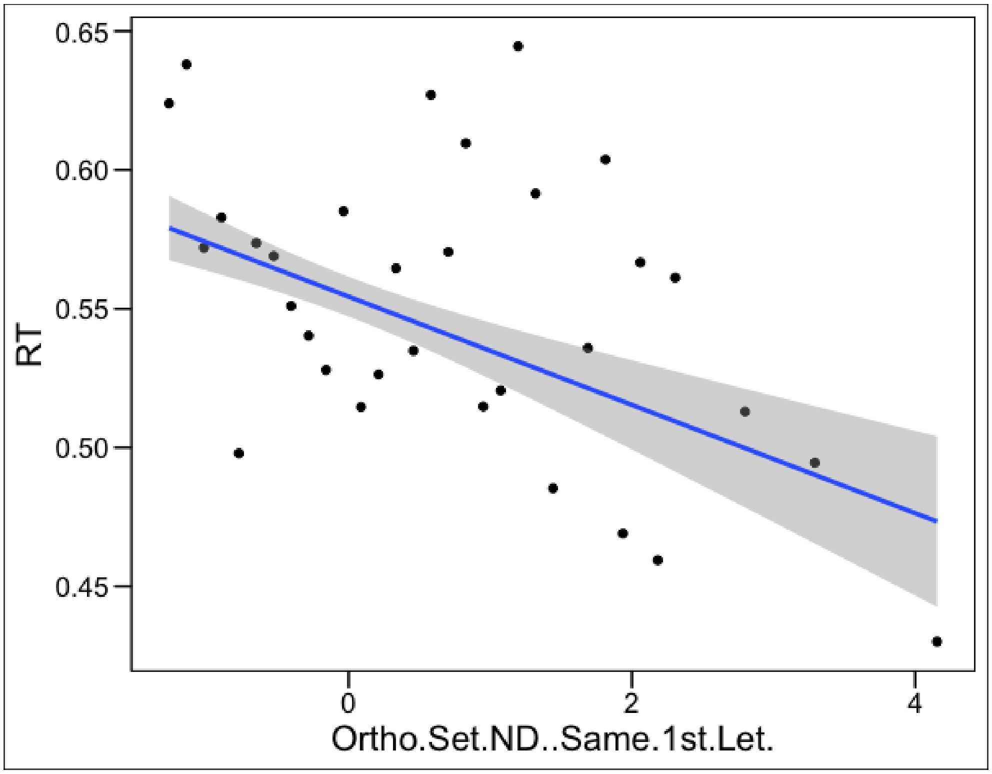


Fig 9. String ND increased RT in *slow* participants

Table A4.5. Slow mean IKI analyses set ND shared first letter & set ND shared first letter & same length

	Dependent variable:	
	meanIKI	
	(1)	(2)
TrialInBlock	-0.002	-0.002
	(0.001)	(0.001)
LgSUBTLWF	-0.004**	-0.003*
	(0.002)	(0.002)
Concreteness_Rating	-0.001	-0.001
	(0.002)	(0.002)
BigramMean	-0.005**	-0.004**
	(0.002)	(0.002)
Ortho.Set.ND..Same.1st.Let.	0.003*	
	(0.002)	
Ortho.Set.ND..Same.1st.Let..SameLength		0.002
		(0.002)
Constant	0.216***	0.216***
	(0.008)	(0.008)
Observations	3,317	3,317
Log Likelihood	4,167.820	4,166.969
Akaike Inf. Crit.	-8,317.639	-8,315.939
Bayesian Inf. Crit.	-8,262.678	-8,260.977
Note:	*p<0.05; **p<0.01, ***p<0.001	

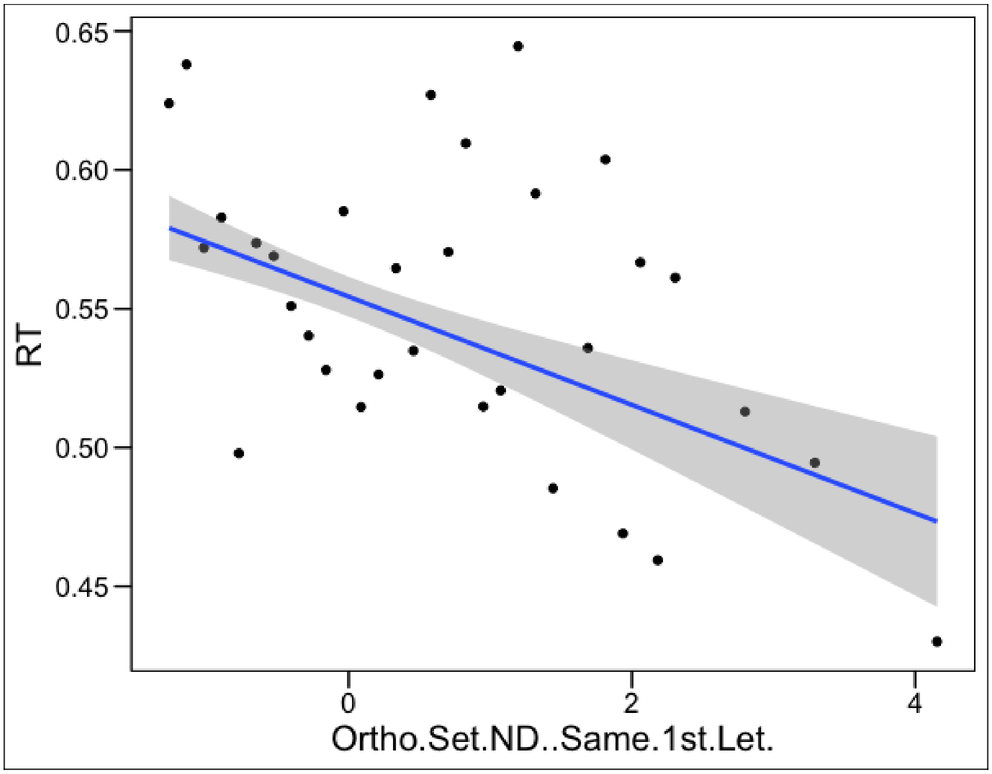


Fig 10. Set ND shared first letter decreased RT in *slow* participants

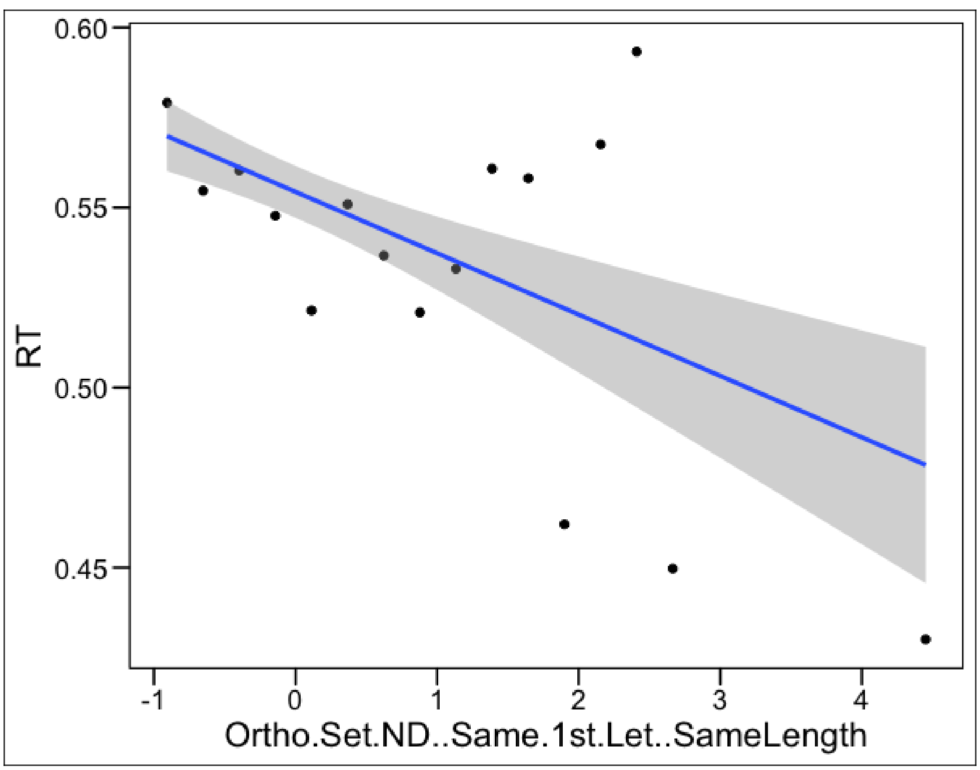
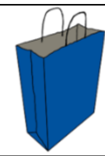
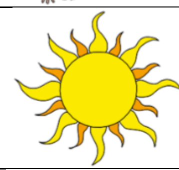
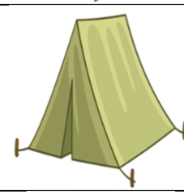


Fig 11. Set ND shared first letter & same length decreased RT in *slow* participants

Appendix B. Supplementary experiment materials

B1. Examples of stimuli

bag	
rat	
sun	
tent	
vest	

B2. Description of measures

Trial Number refers to the order at which an item was presented to the participant within a speech or typing block. Baayen and Milin (2010) noted that there are temporal dependencies between successive trials in many experiments. They argue that the inclusion of trial number in the model helps improving the fit and clarifying the role of the predictors of interest.

LgSUBTLWF is the log transformed SUBTLWF frequency norms. The SUBTLUS corpus is a new frequency measure that is a compilation of 51 million American words (Brysbaert & New, 2009). SUBTLWF is the SUBTLEX word frequency per million words. It is a measure that is used in manuscripts because it is a standard measure of word frequency independent of corpus size. High frequency words are perceived and produced faster and more efficiently than low-frequency words. They are easier to recall yet more difficult to recognize in episodic memory tasks (Brysbaert, et al., 2000).

Concreteness refers to the degree to which a word or concept is perceived as having a tangible, physical referent, or a specific, easily imaginable meaning. Research suggests that concrete words are typically processed more quickly and accurately than abstract words (Bonin et al., 2018).

Bigram mean refers to a pair of consecutive graphemes in a written or typed stream. Research has shown that bigrams regulate written production in both adults and children (Kandel et al., 2011).

Phonological/orthographic string neighborhood density refers to refers to the number of similar or related items (neighbors) that can be formed by changing one phoneme/letter in a target word in the same position (e.g., BAG: BAD, BADGE, RAG, SAG). *String neighborhood density same first letter* refers to a word's ND in which all of the words begin with the same first letter (e.g., BAG: BAD, BADGE). *String neighborhood density same length* refers to a word's ND in which all of the words are the same length (e.g., BAG: BAD, RAG, SAG).

Phonological/orthographic set neighborhood density refers to the number of similar or related items (neighbors) that can be formed by changing one phoneme/letter in a target word, position not specific (e.g., BAG: CAB, GAL, GANG). *Set neighborhood density same first letter* refers to a word's ND in which all of the words begin with the same first letter; lastly, *set neighborhood density same length* refers to a word's ND in which all of the words are the same length (e.g., BAG: CAB, GAL).

Appendix C. Additional analyses

1. Typing results

		RT	Mean IKI
By condition	Online	N.S.	N.S.
	Offline	N.S.	N.S.
By length	Three letter words	N.S.	N.S.
	Four letter words (CVCC/CCVC)	Set ND is *facilitatory*	N.S.
By target word frequency	High frequency words	Set ND is *facilitatory*	Set ND is *inhibitory*
	Low frequency words	String ND is *inhibitory*	String ND is *facilitatory*