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The Dynamic Range of Response Set Activation During Action Sequencing

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We show that theories of response scheduling for sequential action can be discriminated on the basis of their predictions for the dynamic range of response set activation during sequencing, which refers to the momentary span of activation states for completed and to-be-completed actions in a response set. In particular, theories allow that future actions in a plan are partially activated, but differ with respect to the width of the range, which refers to the number of future actions that are partially activated. Similarly, theories differ on the width of the range for recently completed actions that are assumed to be rapidly deactivated or gradually deactivated in a passive fashion. We validate a new typing task for measuring momentary activation states of actions across a response set during action sequencing. Typists recruited from Amazon Mechanical Turk copied a paragraph by responding to a "go" signal that usually cued the next letter but sometimes cued a near-past or future letter ($n-3$, -2, -1, 0, $+2$, $+3$). The activation states for producing letters across go-signal positions can be inferred from RTs and errors. In general, we found evidence of graded parallel activation for future actions and rapid deactivation of more distal past actions.

Public Significance Statement

During a paragraph typing task, we interrupted typist's action planning by shifting them to an unexpected location in a word, forcing them to restart typing at the cued letter. Reaction times were fastest when the cue indicated the expected next letter in a sequence, and increased in a graded fashion as the cued letter moved away from the expected next letter. These findings contribute to our basic understanding of the processes enabling actions to be produced in an intended order, and are consistent with inhibitory theories suggesting that planned responses in a sequence inhibit one another allowing more active responses early in a sequence to be produced before less active responses later in a sequence.

Keywords: serial order, response scheduling, Amazon Mechanical Turk, motor control, skilled typing

The ability to produce actions in series over time is fundamental to performance. For example, ordering action is necessary for routine skills from walking, talking, writing, typing, tying shoes, and making coffee, to dazzling ones in the arts, dance, music, and sports. How ordering processes produce actions in sequence persists as an unresolved aspect of the long-standing serial order problem (Lashley, 1951). Currently, there are many models specifying how action sequences are produced, but few empirical tests to discriminate between model assumptions. We identify the issue of response set dynamics as fertile ground for testing major divides in assumptions between models. *Response set dynamics* refers to momentary changes in the activation levels of action units during production of a series of actions. All models make similar predictions about the momentary activation levels for actions that win the response competition race and are ultimately produced: Each response winner had the highest activation level at each moment in time. However, models make different predictions about the momentary activation levels for the other responses in the race. Some models allow parallel activation of responses and assume a wide range of activation dynamics across the response set, and others use serial triggering of responses and assume a narrow range of activation dynamics across the response set. We introduce a new behavioral tool using typing performance as a proxy for response scheduling that measures the activation states of completed, current, and to-be-completed responses as they change during production of an action sequence. The measure traces the width of activation dynamics across responses in a set and provides a novel means to distinguish models of action sequencing.

The Response Race Metaphor for Sequencing Actions

People routinely produce many kinds of action sequences to achieve various task goals. Functionally speaking, this ability requires a set of responses and a sequencing process for outputting

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them in a desired temporal order. Traditionally, the production of single responses are understood in terms of race models, in which evidence for a response accumulates over time until a threshold triggering the action is reached (Laming, 1968; Ratcliff, Van Zandt, & McKoon, 1999; Smith & Vickers, 1988). We use a race metaphor for the sequencing of multiple actions to highlight critical distinctions between models of the sequencing process.

This simple metaphor can be understood in the context of discussing the general patterns of activation that can occur when executing a sequence of serial responses. In this sense, the runners act as individual elements of an action sequence, and the finish line represents the execution of an element. The problem of explaining the sequencing process is to delineate how different responses cross the finish line (e.g., reach their execution threshold) in desired orders and times. Different models of the sequencing process all accomplish the functional goals of action sequencing, but do so according to different processing assumptions. Prior work has empirically tested model assumptions by measuring directly observable aspects of action sequencing, such as the accuracy and timing of responses. That is, they measured the timing and order of the winners as they crossed the finish line. Critically, models make different assumptions about the activation states of other responses in the race; however, the activation values of other responses are never measured directly, but are usually inferred by patterns of errors among the winners.

To highlight fundamental differences between models of sequencing, we distinguish between two kinds of races for serial order: the 100-yard dash versus a relay race. In the 100-yard dash, all runners line up and race toward the finish line in parallel. In a relay race, the runners are staggered apart from one another, and begin running when the baton is in reach. In both races, the timing and order of the responses is determined by the timing and order of runners as they cross the finish line. The two races emphasize different kinds of control over finishing orders. A real-world 100-yard dash does not control order in the sense that all of the runners are trying to win first place. However, orders could be established by a process that coordinates individual running speeds over the course of the dash such that particular runners finish in particular places. In a relay race, there are multiple finishing lines corresponding to locations on the track where runners within a team hand off the baton, and control over ordering is determined by initial starting positions of the runners. The crucial difference between races is whether runners are running in parallel or in series one at a time, and the crucial difference between models of action sequencing is whether they assume parallel or serial activation of responses within a response set. Before describing individual models, we first illustrate general predictions for response set dynamics that distinguish between serial and parallel models.

As mentioned previously, response set dynamics refer to the activation states of individual action units as they change over time during the course of producing a sequence of actions. Hypothesized response set dynamics for serial and parallel ordering processes are illustrated in Figure 1, which shows the hypothesized activation states of individual responses in a five-element sequence across time.

At the first time point, the serial process depicted in Figure 1A activates the first response. Responses that reach threshold serve as the triggering function for three events: the production of the response, the self-termination or inhibition of that response, and the activation of the next response. This domino-like process continues for all responses in the sequence. Importantly, the dynamic range of activation states for all responses is always narrowly focused around the current response. The current response reaches threshold, deactivates, and triggers the activation of the next response, but not more distal responses.

The parallel process depicted in Figured 1B activates the first response, and also prescribes graded activation levels for the remaining responses. The parallel model makes similar predictions about the fate of completed responses, suggesting they are self-terminated. Importantly, the dynamic range of activation states for all responses is not narrowly focused around the current response, but extends to the more distal responses.

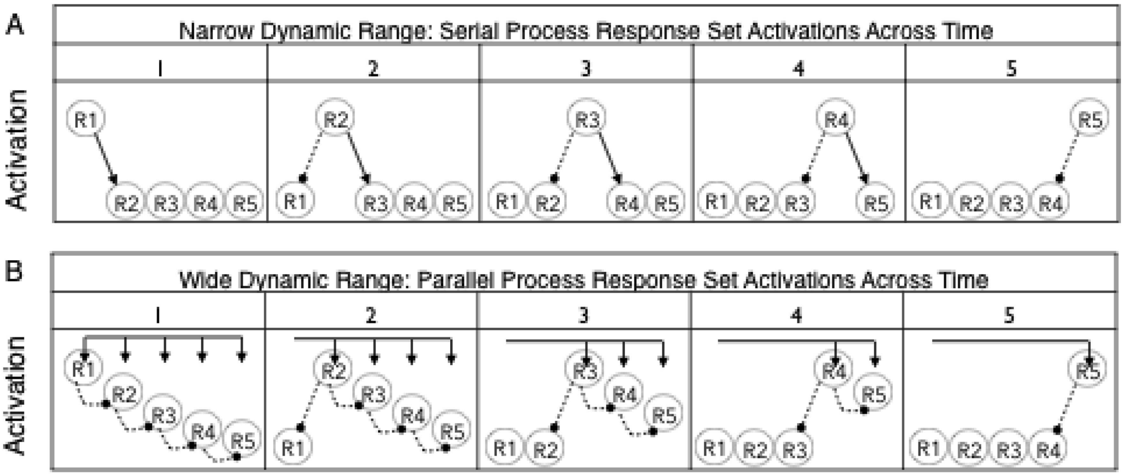

Figure 1. The figure shows hypothesized activation states of all responses in a sequence across moments in time. Figure 1A shows predictions for a serial model, in which only one action is activated at a time, showing a narrow dynamic range. Figure 1B shows predictions for a parallel model in which all future actions are activated in a graded fashion, showing a wide dynamic range.

Serial Versus Parallel Processing Assumptions in Models of Action Sequencing

The problem of explaining how actions are sequenced spans decades of research and has generated several theoretical approaches to the problem. Each of the models invoke processing assumptions that fall on either side of the serial versus parallel distinction and assume narrower or wider dynamic ranges for the activation levels of distal responses during response sequencing. Here, we provide a review of several of the pertinent models.

Associative Chains

Prior to the cognitive revolution serial ordering was explained by associative chains (Washburn, 1916; Watson, 1920). Here, a stimulus serves as the triggering condition for a response: Feedback from action n serves as that triggering condition for action $n+1$, $n+2$, and so on. Associative chain models have been widely criticized (Lashley, 1951; see also Rosenbaum, Cohen, Jax, Weiss, & van der Wel, 2007), particularly as explanations of complex sequencing behavior as seen in language or music production. Nevertheless, simple chaining models exemplify the general predictions of a serial control process for ordering. Specifically, they predict a narrow dynamic range for the activation values within a response set, because a next action is only activated by a previous action. As a result, more distal responses in the chain are not activated in advance of the preceding triggering condition.

Hierarchical Representations

The inability of simple associations to explain complex feats of action sequencing contributed to the rise of cognitive explanations using planning processes to explain ordering (Lashley, 1951; Miller, Galantner, & Pribram, 1960; Tolman, 1948). A common feature of planning models is the assumption of hierarchical representation, in which higher order goal states (e.g., make a sandwich) trigger nested lower order goal states (go to the kitchen, find the bread), and lower ones (open the bag, reach-in, etc.), and so on. Some models using hierarchical representations rely on a serial triggering process and imply a narrow dynamic. For example, Rosenbaum, Kenny, and Derr (1983) illustrated two ways in which responses might traverse through a hierarchically organized sequence. They described a linear read-out process whereby a current response serves as the trigger for the next response (similar to an associative chain). They also described a tree-traversal process whereby the superordinate control nodes connecting groups of response serves as the triggering condition for the next response. The tree-traversal and linear read-out processes make different predictions about the finishing times between responses; however, they make the same predictions about momentary response set dynamics. Specifically, they both imply a serial-triggering process whereby distal future responses are not activated early in the sequence, but are only activated by their preceding triggering condition.

Hierarchical models could be modified to introduce a wider spread of activation across the response set. For example, Cooper and Shallice (2000, 2006) computationally implemented a hierarchical model of the everyday task of making coffee. Their model has many nested levels of goal, subgoal, sub-sub-goal, and so forth nodes that eventually control actions. The specific triggering conditions for a particular action are not unitary because the activation value for a particular response depends on inputs from multiple higher order goal states; thus, the activation levels of all possible responses vary dynamically beyond the range of the most current responses.

Serial-Recurrent Networks

More complex associative models like serial-recurrent neural networks (SRNs; Elman, 1990) can also be trained to produce sequences of varying complexity. For example, SRNs have been used to explain performance in the serial reaction time (RT) task (Cleeremans, 1993), in which people show implicit learning of sequential regularities. As well, Botvinick and Plaut (2004, 2006) showed that an SRN can model routine tasks like coffee making (when trained on appropriate inputs reflecting the constraints of coffee making in a natural environment) without invoking hierarchical representations. The SRN is a flexible model and, in principle, could be constructed to predict activation values for a single or multiple upcoming response(s). So, from an SRN perspective, the width of the dynamic range of the response set during response sequencing is a free parameter.

Competitive Queuing

Competitive queuing models assume that responses are activated in a buffer (queue) and then compete for production by a dynamic mutual inhibition process that determines the order of responses. For example, Estes (1972) proposed that memory for sequences originates from the order in which items are rehearsed during encoding. Rehearsal was described by an inhibitory process that could suppress rehearsal of any item. To rehearse items in sequence, inhibition for particular items would be released one at a time, and the remaining items would remain suppressed. Depending on how inhibition is applied, Estes's description of competitive queuing could produce either narrow or wide ranges of activations for responses in a sequence.

Rumelhart and Norman's (1982) model of skilled typing implements a version of competitive queuing that clearly allows for a wide dynamic range of activation and inhibition. In their model, word units cause parallel activation of letter units, and each letter unit controls individual finger movements to type the key on the keyboard. As a result, fingers can, in principle, move in parallel toward the keys in proportion to their activation level. This, of course, creates a problem for outputting the letters of word in a desired order. Order is achieved by a mutual inhibition process that establishes an activation gradient across the letters in the word: The first letter inhibits all remaining letters, the second letter does the same, and so on. Letters with the highest activation value are typed when their finger has moved to their correct location. Letter units become deactivated after they have triggered a keystroke. Similarly, more recent hierarchical competitive queuing models (Bullock, 2004; Bullock & Rhodes, 2003) are consistent with wide dynamic ranges of activation in response sets during sequencing because they assume parallel activation and lateral inhibitory connections that apply across all responses.

Oscillator Models

Oscillator models use timing signals to control the order of responses. For example, Brown, Preece, and Hulme (2000) distinguish between response units that activate to produce specific actions, and an oscillator-based timing system that controls the order and timing of response unit activation. Oscillator models assume that different responses are triggered at different times by specific clock states. For example, while typing the word “CAGE,” the 12:00 position could trigger the first letter “C.” Other clock positions would trigger the remaining letters, and the temporal differences between the clock positions would further determine the specific intervals between the responses. Oscillator models could be consistent with either a narrow or wide dynamic range of response set activations during sequencing. A narrow range is consistent with a highly precise temporal control signal that causes activation only during the prescribed moment: When the moment occurs, the chosen response is activated, but the other responses are not. A wide range is consistent with a diffuse temporal control signal that causes a gradient of activation around the prescribed moment: Activation for the chosen response grows as the moment approaches, and activation builds for all remaining responses depending on the proximity to their temporal control signal.

Summary

All of the aforementioned models make predictions about the width of the dynamic range of activation and inhibition across a response set during action sequencing. The models fit into two classes of race metaphors in which runners run in series, like a relay race, or in parallel, like a 100-yard dash. Prior empirical work has largely evaluated model predictions in terms of the timing and order of runners (responses) as they cross the finish line. We propose that another key distinguishing feature between models is the dynamic range of activation across the response set at any given moment during sequence execution. If the response race could be paused whenever an action is produced, then the states of the remaining responses could be observed to determine the width of the dynamic range. Serial models suggest a narrow range because only the next response is activated by a previous response, and the remaining responses are not activated. Parallel models suggest a wider range because all of the upcoming responses are in some state of activation. The major aim of this article is to provide a new behavioral measure of the dynamic range of activation of responses during action sequencing. A measure of the dynamic range could discriminate between serial versus parallel models and place new constraints on models that are capable of flexibly producing wide or narrow ranges.

Prior Empirical Work

Measuring the dynamic range of activation across a response set at a particular moment in time is challenging because withheld responses that may have varying activation states are, by definition, not behaviorally observable. An ideal measure would continuously record activation states of all responses in a response set during action sequencing. We review examples from prior work that approximate the ideal measure, and then present our own method for inferring momentary response set activation from RT data.

Perhaps the most direct evidence for parallel models of action sequencing comes from Averbeck, Chafee, Crowe, and Georgopoulos (2002), who used single-unit recording to measure firing rates of neuronal ensembles in the prefrontal cortex (PFC) while monkeys drew simple shapes like squares. They classified neurons coding unique movements to produce different line segments and plotted firing rates over time as the shape was produced. Prior to drawing, they showed that all neuronal populations were firing (as if in parallel), and that firing rates corresponded with serial order for the upcoming movements. These findings are consistent with parallel models predicting a wide dynamic range of response set activation. Serial models would not predict above baseline firing rates for neuronal populations assigned to line segments beyond the first one. During drawing, firing rates peaked in series over time as each line segment was produced. Firing rates for neuronal populations assigned to an immediate next segment sometimes appeared to rise immediately after a prior segment was completed (as if being released from inhibition), and sometimes appeared to gradually rise in parallel before completion of a prior segment—a finding that is also consistent with a wide dynamic range of response set activation.

Using Typing to Measure Dynamic Range of Response Set Activation

Skilled typing ability is a convenient domain for examining processes involved in sequencing actions (for a recent review, see Logan & Crump, 2011). Typing naturally requires action sequencing, and measurements of the timing and accuracy of each action can be measured precisely from computer keyboards. Moreover, typing is a common skill and skilled subjects are readily available. Both behavioral and noninvasive neuroimaging studies of skilled typing lend support to parallel models of action sequencing.

As mentioned previously, Rumelhart and Norman’s (1982) model of typing assumes keystrokes are sequenced by a competitive queueing process: All letters in a word are activated in parallel, and then lateral inhibitory connections allow keystrokes to be executed in order. Two recent studies showed behavioral evidence in favor of the parallel activation hypothesis. Crump and Logan (2010b) presented subjects with a word prime followed by a single-letter probe. They showed faster RTs for single letters from the first, middle, and last position of the word prime compared with unprimed letters. This finding is consistent with the idea that a word causes parallel activation of its constituent letters. Furthermore, priming effects were larger for the first than middle and last letters, consistent with the competitive queueing idea that later responses are inhibited by earlier ones.

Snyder and Logan (2014) showed that parallel activation of letters is constrained by their position in a word. They presented subjects with a word prime followed by a word probe. The probe matched the prime, was an anagram (same letters different order) of the prime, or was an unrelated word (different letters). They showed faster response times to type the probe only to the extent that probe letters matched in both identity and order. They argued that the absence of priming for anagrams was not consistent with positional coding models that independently represent action identity and position: Anagrams should have activated the response identities, and that influence should have carried forward to influence response times during sequencing. They suggested their data was more consistent with associative chaining because priming was only observed for probes containing full or partial chains that could be triggered by the prime.

One recent electroencephalography study also showed evidence consistent with a wide dynamic range of response set activation during typing. Logan, Miller, and Strayer (2011) had subjects type four letter words that required one or both hands. Bimanual words started with two or three letters from one hand, with remaining letters from the other hand. They measured lateralized readiness potential (LRP), an indication of preparatory motor activity for one side of the body, time locked to the first keypress. LRP amplitudes leading up to the first keystroke were larger for unimanual words compared with bimanual words, with smaller amplitudes for words containing more letters from the other hand after the first keystroke. The LRP results are consistent with parallel activation of keystrokes beyond the first one, and are suggestive of a wide dynamic range because LRP amplitude depended on the amount of future keystrokes from one hand in the word.

Amazon Mechanical Turk

All subjects in each experiment were native English speakers and were recruited via Amazon's Mechanical Turk (AMT), an online crowd-sourcing website. Subjects were compensated $1.00 for participating and could only participate in the experiment once. If a subject failed to complete the experiment, they could not start over or resume at a later time. The experiments were programmed in JavaScript and HTML and run locally in subjects' web browsers.

AMT affords the opportunity to collect data from large, diverse samples of the population, both quickly and inexpensively; however, employing AMT precludes the ability to control for certain factors that would normally be controlled in the laboratory. For example, visual angle and distance from the screen are left up to the testing subject. Additionally, different web browsers and screen resolutions result in the possibility that the materials may not be rendered the same for all subjects. Subjects are likely using different computers and completing the task in their own time, with different typing styles (e.g., touch typing, hunt and peck). Finally, we are unable to control for environmental distractions. However, even with these limitations, AMT has been shown to be a reliable data collection tool. Crump, McDonnell, and Gureckis (2013) validated this online method as tool for conducting behavioral experiments requiring millisecond precision for measuring RTs (see also Barnhoorn, Haasnoot, Bocanegra, & van Steenbergen, 2014; Reimers & Maylor, 2005; Reimers & Stewart, 2015; Schubert, Murteira, Collins, & Lopes, 2013; Simcox & Fiez, 2014). Additionally, Behmer and Crump (2015) have validated the approach for measuring performance in continuous typing tasks.

Present Aims

We have identified the dynamic range of response activation for all responses in an action sequence as an issue that can discriminate between models of action sequencing. We are not aware of prior work, especially in human behavior, that has systematically measured the dynamic range of response set activation over the entire course of action sequencing. We report a modified go-signal procedure that measures momentary response set activation, and examine evidence for wide or narrow dynamic ranges in skilled typing. Although our present efforts are limited to sequencing in typing, we expect that the general issue of determining dynamic range of response set activation is broadly applicable to other sequencing tasks.

Experiment 1: Typing Words

Our procedure borrowed from prior work on stopping and online revision during typing. Typists can quickly stop typing when presented with a stop signal, even when they are in the middle of a word (Logan, 1982; Salthouse & Saults, 1987). And when to-be-typed words are changed midway through typing, some typists are able to revise their plan and resume typing quickly (Shaffer, 1988).

Combining these two procedures, we had typists stop typing in the middle of a sequence and then immediately restart from different positions in the sequence. Typists were presented with a paragraph of text and copied letters by following a go-signal that turned cued letters red. The red letter was usually the next letter in the sequence. However, occasionally the go-signal cued letters that were plus or minus one to three letters away from the expected next letter. The measures of interest were RTs and error rates for resuming typing at each serial position cued by the go-signal.

In general, we assume that the activation states governing particular actions can be inferred from RTs and error rates. Strongly activated action plans lead to faster RTs than weakly activated, or inhibited, action plans. Similarly, strongly activated action plans can also lead to errors when activation levels for an incorrect action are greater than activation levels for a correct action. So, the pattern of RTs and error rates across go-signal positions can be used to infer momentary activation states of individual responses in a current response set.

Models of action sequencing that predict a narrow or wide dynamic range of response set activation make contrasting predictions for performance in our task. Idealized predictions that are broadly representative of predictions from each class of models are illustrated in Figure 2. Importantly, both completed and future responses can show activation states that are either wide or narrow. For example, Panel D shows how future responses may be activated along a narrow range, with the immediate response being active and future responses being inactive or inhibited. Conversely, Panel C shows future responses being active along a wide range, with the current response being most active and future responses displaying increased activation across a gradient. These same predictions are applicable to completed actions as well (Panels A and B). Additionally, activation states between completed and future responses may not necessarily be symmetrical. For example, Rumelhart and Norman (1982) suggest that previous responses in a sequence are actively inhibited, which would produce a pattern similar to Panel C. The fastest RT is for the current letter in the sequence, and all recently typed letters are assumed to be deactivated, so RTs would be similarly slow for all of those serial positions. Conversely, future responses are competitively queued across a wide dynamic range, similar to Panel B, so their RTs systematically increase as a function of serial position. These general predictions were tested in the following five experiments.

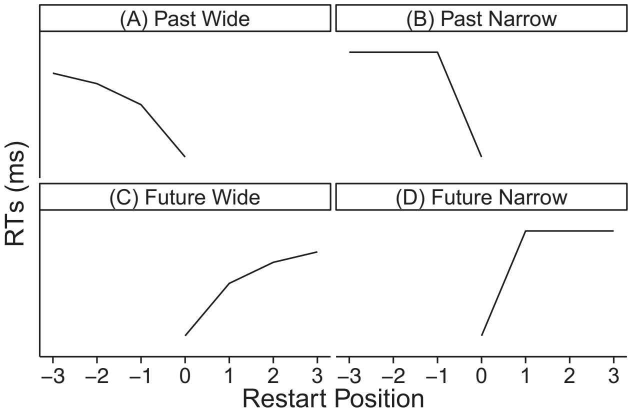

Figure 2. General predictions for reaction times (RTs) for past and future responses from wide or narrow models of action sequencing when stopping typing and restarting in a different position. Narrow, or serial, models predict that a completed action triggers the next, so only the fastest response should be Position 0, which reflects the expected next letter in a sequence. All future responses are not yet activated, and all past responses are deactivated, so RTs are equivalent. Wide, or parallel, models predict some graded activation for all future responses in the set, as well as the possibility of gradual deactivation for completed responses. Importantly, some models predict that future and past responses in a sequence can differ across wide or narrow activation states. For example, Rumelhart and Norman (1982) predict that future actions are activated across a wide dynamic range, consistent with competitive queuing models (Panel B), whereas past responses are rapidly deactivated, consistent with a narrow range model for past responses (Panel C).

Method

Subjects. Fifty subjects participated in Experiment 1. Seven subjects failed to complete the task. Four subjects were rejected from the final analysis for failing to meet minimum accuracy and speed requirements (minimum 80% accuracy and 1,250-ms average RTs). These subject exclusion criteria were applied consistently across all experiments. The remaining 39 subjects (mean age = 38 years, *SD* = 11; 26 female, 12 male, one undefined) reported having been typing for 21 years (*SD* = 10 years), and started typing at 14 years old (*SD* = 6 years). Thirty-seven were right-handed (one left-handed, one undefined), 24 reported that they had received some type of formal typing training during K-12 education (15 indicated “no”), and 34 reported being able to touch type (five indicated “no”).

Apparatus and stimuli. The experiment was programmed using JavaScript and HTML. The program allowed subjects to complete the task only if they were running Safari, Google Chrome, or Firefox web browsers. Each experiment ran as a pop-up window that filled the entire screen. The paragraph was presented in the center of the screen in 20-point Helvetica font. Text was black presented against a gray background. The go-signal cue was colored red. Subjects typed one paragraph (approximately 115 words) chosen randomly from a set of 10 paragraphs about border collies, taken from Logan and Zbrodoff (1998).

Design. Typists were presented with the paragraph and instructed to respond to each letter as soon as it turned red. The first letter in the paragraph was displayed in red. Each response (correct or incorrect) triggered the next go-signal, with a jittered delay (200 ms +random value between 0 and 300). The delay was included to maintain vigilance and provide subjects with enough time to detect the signal.

In general, most of the go-signals cued the immediate next letter in the sequence, referred to as Position 0 throughout the manuscript. The first 10 letters in a paragraph always cued Position 0. After the first 10 letters, the go-signal cued the expected next letter 50% of the time, or another position between plus or minus one to three letters from Position 0 (with equal probability). For example, consider being cued to type “r” in the string, “The natural wo**r**king ability. . . .” After typing “r,” there was a 50% chance the go-signal would cue the next letter “k,” or a roughly 8% chance it would cue letters plus or minus one to three letters from “k” (−3 = w, −2 = o, −1 = r, +1 = i, +2 = n, +3 = g). Go-signals always cued characters and never cued spaces. Whenever a go-signal cued a shifted letter (e.g., not Position 0), the following four go-signals always cued the expected next letter (Position 0).

Procedure. All subjects were AMT workers who found the experiment using the AMT system. The subject recruitment procedure and tasks were approved by the Brooklyn College Institutional Review Board. Each subject read a short description of the task and gave consent. Subjects then completed a short demographic survey and proceeded to the main task, in which they were shown instructions and a to-be-typed paragraph. Subjects were instructed to begin by typing the red letter, and then wait for the next red letter and type it as quickly and accurately as possible. They were also told that the red letter would usually be the next letter in the sequence, but sometimes it would be a different letter.

Results and Discussion

We collected accuracy and RT data for all five experiments. For Experiment 1, correct RTs at each go-signal position for each subject were submitted to an outlier elimination procedure (nonrecursive; Van Selst & Jolicoeur, 1994) that removed an average of 3% of observations. Our objective was to investigate whether changes in activation states occurred across wide or narrow dynamic ranges. In order to accurately assess these differences, we needed to address two possible confounds. First of all, if subjects were shifted to a go-signal position where the letter they were shifted to was the same letter they were planning to type in the expected location, those trials were removed from the analysis. For example, when subjects were typing the word “BELIEVED,” if after typing “V,” subjects were shifted to the “E” at Go-Signal Position −2 (the “E” that appears before “V”), that trial would be removed because we could not discriminate whether the RTs for that response represented the activation state of Go-Signal Position 0, or Go-Signal Position −2. Furthermore, we removed trials in which the letter that was to be typed also appeared within a plus or minus three-letter window surrounding the response. For example, returning to the word “BELIEVED,” when typing the middle “E,” it is difficult to parse out the influence the completed and future “E” may have on the current “E” being typed. This removed an average of 26% of observations from each condition. Table 1 shows the number of trials at each go-signal position analyzed for all five experiments. Mean RTs for each participant at each go-signal position were then submitted to separate repeated measures ANOVAs, with go-signal position as the sole factor.

Table 1
Number of Trials at Each Go-Signal Position in Each Experiment

Experiment	−3	−2	−1	0	1	2	3
Experiment 1	352	344	314	11,808	304	327	349
Experiment 2	394	401	373	15,662	375	198	420
Experiment 3	487	494	497	15,492	491	498	496
Experiment 4	276	278	359	10,618	270	269	285
Experiment 5 (p)	380	348	354	35,671	242	326	382
Experiment 5 (u)	514	474	472	417	467	474	475

Note. For Experiment 5, “p” is the number of observations at each go signal for responses that were a part of the original sequence, and “u” is for unplanned responses.

Mean RTs as a function of go-signal position are displayed in Figure 3A. The main effect of go-signal position was significant for RTs, $F(6, 222) = 70.4$, Mean Squared Error (MSE) = 9,799, $p < .001$, $\eta_p^2 = 0.66$. The pattern of RTs across go-signal positions appeared roughly symmetrical for completed (−1 to −3) versus future (+1 to +3) actions. Each of these are analyzed in turn with planned comparisons.

We predicted that the dynamic range of response set activation could be measured by the pattern of RTs across past and future go-signal positions. A narrow dynamic range assumes that only the immediate next action (Go-Signal Position 0) is activated. A wider dynamic range assumes graded activation across future actions; however, all models similarly predict that responses rapidly deactivate after completion. Thus, RTs should be equally slow across all completed go-signal positions.

RTs. Subjects were faster at Go-Signal Position 0 ($M = 535.8$, Standard Error (SE) = 16.2) compared with Go-Signal Position +1 ($M = 815.1$, $SE = 26.2$), $t(37) = -17.57$, $p < .001$, and Go-Signal Position −1 ($M = 819.1$, $SE = 26.9$), $t(37) = 11.68$, $p < .001$. Additionally, they were faster at Go-Signal Position +1 compared with Go-Signal Position +2 ($M = 890.6$, $SE = 29.1$), $t(37) = -3.39$, $p < .001$. However, there was no difference between RTs at Go-Signal Position +2 compared with Go-Signal Position +3 ($M = 920.5$, $SE = 27.9$), $t(37) = -1.15$, $p = .26$. Subjects were faster at Go-Signal Position −1 compared with Go-Signal Position −2 ($M = 877.6$, $SE = 23.4$, $t(37) = 2.54$, $p = .02$. Finally, subjects were faster at Go-Signal Position −2 compared with Go-Signal Position −3 ($M = 920.5$, $SE = 27.9$), $t(37) = 2.72$, $p = .01$.

RTs for completed and future responses show evidence in favor of a wide dynamic range. As predicted by both classes of models, RTs were fastest at Go-Signal Position 0, which was always the expected next letter that should have been most activated. Additionally, RTs for Go-Signal Position +1 were faster than Position +2; however, RTs for Position +2 were not faster than Position +3. This pattern is consistent with graded activation of responses across a wide dynamic range.

Conversely, the observed pattern of RTs for completed actions did not conform well to idealized model predictions. Specifically, if all completed actions were immediately deactivated, then we would have expected RTs to be equally slow for Positions −1 through −3. Instead, we observed graded RTs across those positions. One possibility is that deactivation of a completed response unfolds gradually over time. Regardless, the pattern for completed actions is consistent with graded activation of responses across a wide dynamic range. This is consistent with findings from Averbeck et al., (2002) in which firing rates of neurons in the monkey PFC did not immediately cease after monkeys completed drawing a line, but instead gradually went back to baseline over a span of 200 to 500 ms.

One possible interpretation of these findings is that differences in RTs are a function of visual search. During a conjunctive search, RTs show a linear increase as the number of distractors increases. Because the target and distractors share common features, these searches tend to be difficult with a high number of distractors. Conversely, during feature searches, the target and distractors differ by a single property. Even when the number of distractors is large, RTs tend to be fast because the target is easy to detect (A. M. Treisman & Gelade, 1980). If our results were driven by visual search, then the change in go-signal should have produced a pop-out effect, and RTs would have been similarly fast at every go-signal position. Instead we observed a nonlinear, exponential pattern that reflects differences in activation states based on go-signal position. Furthermore, to test for nonlinearity, we compared the fits of linear and exponential functions to the RTs of future go-signal position. For Experiment 1, exponential functions gave better fits ($r^2 = .91$, $p < .03$, AIC = 46.13) than linear functions ($r^2 = .72$, $p < .10$, Akaike’s Information Criterion (AIC) = 50.72).

Errors. The models do not make specific predictions about errors; however, it is reasonable to assume that they would predict that error rates should be highest for the most potent response, which would be the planned letter. Mean error rates as a function of go-signal position are displayed in Figure 3B. The main effect of go-signal position was significant for errors, $F(6, 222) = 12.3$, $MSE = 0.010$, $p < .001$, $\eta_p^2 = 0.25$. The pattern of errors across go-signal positions appeared roughly symmetrical for completed (−1 to −3) versus future actions (+1 to +3).

Overall, errors were low, demonstrating that subjects could perform the task. During Experiment 1, errors were lowest for Go-Signal Position 0, highest for the next closest positions (−1, and 1), and then gradually lower for more distal go-signal positions. Overall, one might expect that subjects would sometimes commit perseveration errors by failing to detect the change in go-signal position and type the letter expected at Position 0 instead of the shifted letter. Figure 4A shows the proportions collapsed

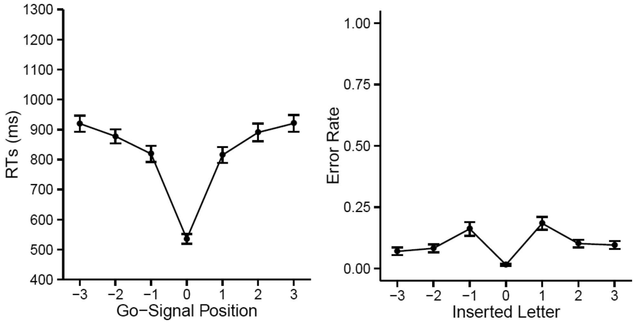

Figure 3. Mean reaction times (RTs; in ms) and error rates, with standard errors as a function of go-signal position for Experiment 1. Go-signal Position 0 refers to the expected next letter in the sequence.

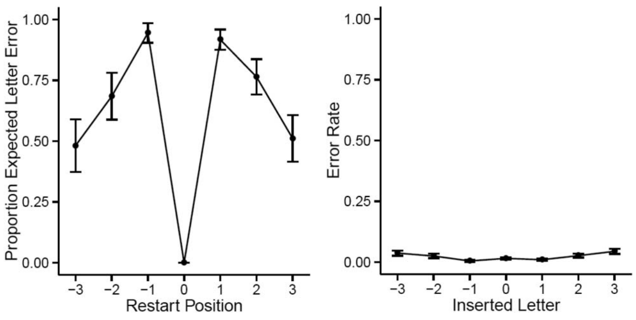

Figure 4. Mean proportion of perseveration errors and mean error rates, with perseveration errors removed with standard errors as a function of go-signal position for Experiment 1. A perseveration error occurs when the letter in the expected go-signal position (0) is typed in place of the cued letter.

across all subjects, including those who did not make at least one error in each position. An ANOVA analysis of perseveration errors was not possible because only 20% of subjects made at least one error in each position; however, according to independent samples *t* tests, Position +1 ($M = 0.92$, $SE = 0.04$) and −1 ($M = 0.94$, $SE = 0.04$) had higher rates of perseveration errors than Positions +2 ($M = 0.76$, $SE = 0.07$) and −2 ($M = 0.68$, $SE = 0.10$), $t(98) = 3.32$, $p < .001$, which had higher rates than Position +3 ($M = 0.51$, $SE = 0.10$) and −3 ($M = 0.46$, $SE = 0.11$), $t(83) = 2.38$, $p = .009$. Figure 4B shows the mean error rates for go-signal position after removing perseveration errors, $F(6, 222) = 3.69$, $MSE = 0.002$, $p < .008$, $\eta_p^2 = 0.09$. Error rates appear linear, with proportional range of errors falling within 0.01 to 0.04. The fact that perseveration errors varied by position is interesting. It may be the case that subjects occasionally missed the go-signal position shift, and the closer the shift was to Go-Signal Position 0, the more likely subjects would commit a perseveration error. Responses to more distal positions may have afforded subjects more time to notice the change, thereby leading to a decrease in perseveration errors and a corresponding increase in RTs.

The wide, graded state of activation we observed in Experiment 1 may have been driven by parallel planning when typing normal English text. Taking away subjects' ability to plan should interfere with their ability to maintain responses in a queue. In Experiment 2, we took away subjects' ability to plan in parallel by having them type random letter strings.

Experiment 2: Typing Random Letter Strings

In Experiment 1, we demonstrated evidence for a wide dynamic response range for both completed and future responses when subjects typed normal word strings. It is well known that random strings of letters are typed much more slowly than familiar words, and tend to be processed serially, as opposed to normal English text, which is processed in parallel (Gentner, Larochelle, & Grudin, 1988; Shaffer & Hardwick, 1968). One explanation for this is that nonwords lack higher order representations capable of activating all letters in parallel; thus, the sequencing process operates like a slow, linear read-out process. For example, Crump and Logan (2010b) showed that words prime the first, middle, and last letters within a word, suggesting that word-level representations cause parallel activation of letter units (Rumelhart & Norman, 1982). They also showed that random letter strings only prime the first letter in the string, suggesting that letter strings without word status do not cause parallel activation of their constituent letters. With this in mind, we would expect the dynamic range of response set activation to be wide for sequences that can be planned in parallel (i.e., a word), and narrow for sequences that are planned without parallel activation (i.e., random letter strings). To further validate our measure we tested this prediction in Experiment 2 by having subjects type a paragraph of random letter strings.

Method

Subjects. Fifty subjects participated in Experiment 2. One subject failed to complete the task. Six subjects were excluded from analysis for not meeting mean accuracy or RT criterion. The remaining 43 subjects (mean age = 36 years, $SD = 12$; 32 female, 10 male, one undefined) reported having been typing for 21 years ($SD = 8$ years), and started typing at 13 years old ($SD = 5$ years). Thirty-five were right-handed (four left-handed, two undefined, two both), 23 reported that they had received some type of formal typing training during K-12 education (20 indicated "no"), and 34 reported being able to touch type (nine indicated "no").

Apparatus and stimuli. The apparatus was the same as Experiment 1. The only difference was that subjects were presented with a paragraph of 120 randomly generated letter strings. Each letter string was five letters in length. Every letter in the alphabet had an equal probability of being selected for each position. Ten paragraphs of random letter strings were generated and one was randomly assigned to each subject.

Design and procedure. The design and procedure were identical to Experiment 1.

Results and Discussion

As with Experiment 1, RTs at each go-signal position for each subject were submitted to an outlier elimination procedure (nonrecursive; Van Selst & Jolicoeur, 1994) that removed an average of 3% of observations. Additionally, an average of 24% of observations were removed from the analysis for trials meeting the confound criteria established in Experiment 1. Mean RTs for each participant at each go-signal position were then submitted to separate repeated measures ANOVAs, with go-signal position as the sole factor.

Mean RTs as a function of go-signal position are displayed in Figure 5A. The main effect of go-signal position was significant for RTs, $F(6, 252) = 90.9$, $MSE = 8{,}546$, $p < .001$, $\eta_p^2 = 0.68$. The general pattern of RTs across go-signal positions resembled those from Experiment 1.

We predicted that typing random letter strings would result in a narrow range of activation for completed and future responses. Because letters would not be planned in parallel, RTs for completed and future responses should be equally slow.

RTs. Subjects were faster at Go-Signal Position 0 ($M = 625.9$, Standard Error (SE) = 23.9) compared with Go-Signal Position +1 ($M = 894.0$, $SE = 27.0$), $t(42) = -16.62$, $p < .001$, and Go-Signal Position −1 ($M = 829.5$, $SE = 25.9$), $t(42) = 11.45$, $p < .001$. There was no difference in RTs at Go-Signal Position +1 compared with Go-Signal Position +2 ($M = 926.0$, $SE =$

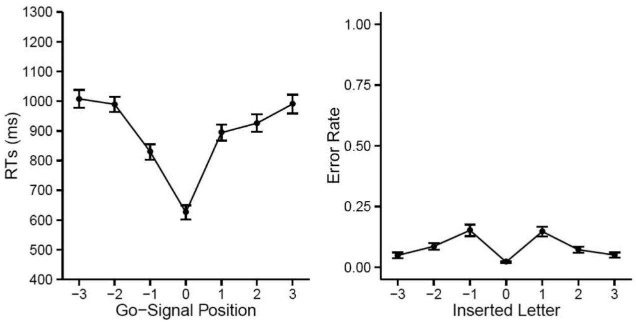

Figure 5. Mean reaction times (RTs; in ms) and error rates, with standard errors as a function of go-signal position for Experiment 2.

29.6), $t(42) = -1.62$, $p = .11$. However, subjects were faster at Go-Signal Position +2 compared with Go-Signal Position +3 ($M = 990.4$, $SE = 31.5$), $t(42) = -3.60$, $p < .001$. Subjects were faster at Go-Signal Position −1 compared with Go-Signal Position −2 ($M = 989.4$, $SE = 25.7$), $t(42) = 8.19$, $p < .001$. Finally, there was no difference in RTs at Go-Signal Position −2 compared with Go-Signal Position −3 ($M = 1007.8$, $SE = 29.8$), $t(42) = 0.98$, $p = .34$.

As with Experiment 1, we did not observe a pop-out effect consistent with single-feature visual search. Additionally, tests for nonlinearity demonstrated that exponential functions gave better fits for the data from Experiment 2 ($r^2 = .90$, $p < .03$, AIC = 45.97) than linear functions ($r^2 = .73$, $p < .00$, AIC = 49.99).

The data from Experiment 2 were not symmetrical like Experiment 1. We performed two post hoc linear contrasts to assess differences in RTs between completed and future go-signal responses. RTs at Go-Signal Position −1 were significantly faster than RTs at Go-Signal Positions +1, +2, and +3, $t(294) = -3.35$, $p < .001$. Additionally, RTs at Go-Signal Positions +1, +2, and +3 were faster than RTs at Go-Signal Positions −2 and −3, $t(294) = 2.44$, $p = .02$.

We expected that random-letter strings would not be planned in parallel and would not show evidence of graded activation across completed and future actions. Instead, we observed that the more distal completed responses (Go-Signal Positions −2 and −3) appear to be rapidly deactivated, whereas future responses appear to show a wide, graded range of activation states. As expected, subjects were always fastest for the most active response at Go-Signal Position 0. Additionally, RTs at Go-Signal Position −1 were faster compared to all remaining go-signal positions, suggesting that subjects experienced a priming benefit in relation to letters at other go-signal positions when shifted back to the letter they just typed.

It is not immediately clear whether the RTs for future responses are at odds with prior work. Crump and Logan (2010b) primed subjects with a random word followed by a single-letter probe that was either the first, third, or fifth letter of the prime word. They observed a priming effect only when the probe was the first letter of the word, and not the third or fifth letter, suggesting that random letter strings are not planned in parallel; however, it may be the case that in Experiment 2, the go-signal position range was narrow enough to enable parallel planning of future responses. This is consistent with previous observations that show that interkeystroke intervals for random letter strings increase in speed as the preview window increases in size, for up to eight letters (Shaffer, 1973).

Errors. Mean error rates as a function of go-signal position are displayed in Figure 5B. The main effect of go-signal position was significant for errors, $F(6, 252) = 13.6$, $MSE = 0.008$, $p < .001$, $\eta_p^2 = 0.24$. The pattern of errors across go-signal positions appeared roughly symmetrical for completed (−1 to −3) versus future (+1 to +3) actions.

Figure 6A shows the proportions of perseveration errors collapsed across all subjects, including those who did not make at least one error in each position. As with Experiment 1, an ANOVA analysis of perseveration errors was not possible because only a few subjects committed perseveration errors at every go-signal; however, according to independent samples *t* tests, Positions +1 ($M = 0.91$, $SE = 0.05$) and −1 ($M = 0.84$, $SE = 0.06$) had higher rates of perseveration errors than Positions +2 ($M = 0.87$, $SE = 0.07$) and −2 ($M = 0.61$, $SE = 0.09$), $t(108) = 2.20$, $p = .03$, which had higher rates than Positions +3 ($M = 0.56$, $SE = 0.11$) and −3 ($M = 0.45$, $SE = 0.12$), $t(79) = 2.27$, $p = .03$. Figure 6B shows the mean error rates for go-signal position after removing perseveration errors. The difference in error rates was not significant, $F(6, 252) = 1.77$, $MSE = 0.002$, $p = .16$, $\eta_p^2 = 0.04$. As observed in Experiment 1, after removing perseveration errors, error rates appear linear, falling within the range of 0.01 to 0.04.

In Experiment 2, perseveration errors were high at Go-Signal Positions ±1 and +2. In Experiment 1, we suggested that the high rate of perseveration errors at Go-Signal Positions ±1 may have occurred because subjects occasionally missed the shift because of the proximity of the shifted letter to the target letter. When considering the perseveration error data from Experiment 2, it may be the case that the potent activation level of the expected letter was directly interfering with the activation states of lesser, but still highly active, elements in the sequence. During Experiment 2, other than responses at Go-Signal Position 0, the next most active responses were the response that subjects just completed (−1) and the next two subsequent response after Go-Signal Position 0 (+1 and +2). It is possible that RTs at shifted go-signal positions reflect the activation state of a letter within a sequence, whereas perseveration errors reflect the potency of position. The increased activation state for the responses at Go-Signal Positions ±1 and +2 are reflected in the faster RTs at those positions compared

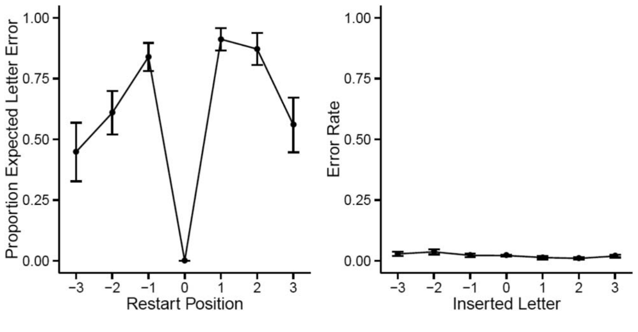

Figure 6. Mean proportion of perseveration errors and mean error rates with perseveration errors removed, with standard errors as a function of go-signal position for Experiment 2. A perseveration error occurs when the letter in the expected go-signal position (0) is typed in place of the cued letter.

with more distal responses. Conversely, the high rates of perseveration errors at those same positions reflect the competitive influence of the expected response on those positions. This may seem counterintuitive, in that one might expect RTs at these positions to be comparatively slow. In a competitive queuing model, early responses in the sequence exert a disproportionate inhibitory influence on later responses. Furthermore, early elements are less inhibited and, as a consequence, are more active relative to distal responses. RTs at go-signal positions where letters may be less inhibited may be indexing the activation states of those letters during a correct response, whereas perseveration errors at these same positions may reflect the difficulty in inhibiting the most active, planned response and executing a lesser, but still highly active, keypress. This might also explain why RTs at the most distal positions are slower and also yield lower rates of perseveration errors. Given that more distal responses are more inhibited, subjects were slower to respond because the response needed to be executed from the ground up. Relatedly, perseveration errors were significantly lower because, in a sense, shifting to a more distal position may be forcing subjects to create a new plan, and as a result, the influence of the letter they were expecting to type becomes less of an interference. Conversely, subjects are faster for more active elements, but when they fail, the least inhibited element, in this case, the expected letter, tends to win the competition for selection.

Although tests of linearity in Experiments 1 and 2 suggest that our results were not driven by visual search, Experiments 3 and 4 were designed to independently assess the role of visual and spatial confounds. In Experiment 3, we removed subjects' ability to preview by presenting them one letter of the normal paragraph at a time, while still occasionally shifting the go-signal position. If the graded RTs for future and completed responses in Experiments 1 and 2 were simply a result of the time it took subjects to locate and respond to the shifted go-signal position, then we would expect to see a similar pattern of RTs for shifted positions in Experiment 3. In Experiment 4, we kept spatial location constant by inserting a letter from a future or completed go-signal position instead of shifting subjects to a different location. If RTs for future and completed responses were driven by spatial positioning, then we would expect to see relatively flat RTs across future and completed go-signal positions.

Experiment 3: Typing Without Preview

A task that measures the dynamic range of response set activation should be sensitive to manipulations that vary whether or not actions can be planned in parallel, and thus receive a wide range of response set activation. To further validate our task, Experiment 2 used random letter strings, which are assumed to be difficult to plan in parallel. However, the results were mixed, showing graded activation of response set activation across future go-signal positions, yet deactivation for more distal completed responses. Experiments 3 and 4 were conducted to provide another line of validation. Wide dynamic ranges should not be possible whenever responses cannot be planned in parallel. In Experiment 3, we eliminated parallel planning by restricting preview of upcoming letters in the paragraph. All of the letters in the paragraph were hidden from view by setting their font color to the same value as the background. Cued letters appeared one at a time in red. Without the ability to plan, we expected to find no evidence of any activation for completed or future actions. However, if results from Experiments 1 and 2 were driven by visual search, then RTs may show a similar pattern, reflecting the time it takes to find a letter when it shifts location. In Experiment 4, we kept the spatial location constant by inserting letters from different positions into the expected location (Go-Signal Position 0). If the "V" pattern from Experiments 1 and 2 were driven by spatial confounds, then we would expect to see flat RTs at completed and future go-signal positions.

Method

Subjects. Fifty subjects participated in Experiment 3. Eight subjects failed to complete the task. Three subjects were excluded from analysis for not meeting mean accuracy or RT criterion. The remaining 39 subjects (mean age = 37 years, *SD* = 12; 27 female, 11 male, one undefined) reported having been typing for 19 years (*SD* = 10 years), and started typing at 15 years old (*SD* = 7 years). Thirty-two were right-handed (four left-handed, three undefined), 22 reported that they had received some type of formal typing training during K-12 education (16 indicated "no," one undefined), and 29 reported being able to touch type (nine indicated "no," one undefined).

Apparatus and stimuli. The apparatus and stimuli were the same as Experiment 1, except that the entire paragraph was never displayed to the subject. Instead, the font color of the letters in the paragraph was set the background gray, rendering each letter invisible, but maintaining the position of each letter within the paragraph. The go-signal cued each letter by turning it from gray to red. Thus, subjects only viewed a single letter at any given time.

Design and procedure. The design and procedure was identical to Experiment 1.

Results and Discussion

As with the previous experiments, RTs in each condition for each subject were submitted to an outlier elimination procedure (nonrecursive; Van Selst & Jolicoeur, 1994) that removed an average of 3% of observations from each condition. Mean RTs for each participant at each go-signal position were then submitted to separate repeated measures ANOVAs, with go-signal position as the sole factor.

Mean RTs as a function of go-signal position are displayed in Figure 7A. The main effect of go-signal position was significant for RTs, $F(6, 228) = 27.9$, $MSE = 3{,}815$, $p < .001$, $\eta_p^2 = 0.42$.

RTs. Participants were faster at Go-Signal Position −1 ($M = 624.7$, $SE = 17.5$) compared with Go-Signal Position −2 ($M = 737.0$, $SE = 24.4$), $t(38) = 6.53$, $p < .001$, and Go-Signal Position 0 ($M = 748.1$, $SE = 22.4$), $t(38) = -8.22$, $p < .001$. There was no difference between Go-Signal Position 0 and Go-Signal Position +1 ($M = 763.7$, $SE = 26.8$), $t(38) = -1.52$, $p = .14$, Go-Signal Positions +1 and +2 ($M = 766.4$, $SE = 24.1$), $t(38) = -0.32$, $p = .75$, or Go-Signal Positions +2 and +3 ($M = 778.7$, $SE = 25.2$), $t(38) = -1.16$, $p = .26$. Finally, there was no difference between Go-Signal Positions −2 and −3 ($M = 755.7$, $SE = 25.6$), $t(38) = 1.51$, $p = .14$.

A post hoc linear contrast confirmed that RTs at Go-Signal Position −1 were faster than the remaining go-signal positions, $t(266) = -5.18$, $p < .001$.

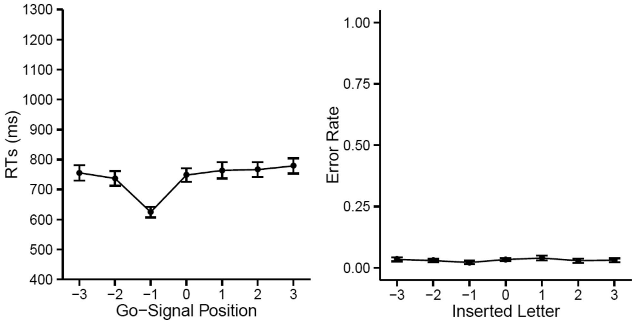

Figure 7. Mean reaction times (RTs; in ms) and error rates, with standard errors as a function of go-signal position for Experiment 3. Critically, Go-Signal Position −1 refers to a repetition of the most recently completed action.

Errors. Mean error rates as a function of go-signal position are displayed in Figure 7B. Because no responses were planned in parallel, there were no perseveration errors to analyze. As expected, there was no main effect of go-signal position for error rates, $F(6, 228) = 0.81$, $MSE = 0.0015$, $p = .56$, $\eta_p^2 = 0.02$, which were all uniformly low.

Without the ability to plan for upcoming letters in parallel, the data clearly show a simple influence of repetition priming. RTs are fastest for Go-Signal Position −1, which was always a repetition of the last response, compared with any other position, which were all similarly slow. Error rates were equally low across go-signal positions.

The remaining RTs for all other go-signal positions maintained a flat distribution, as opposed to the graded activation pattern observed in Experiments 1 and 2, even though changes in spatial position were consistent with the previous two experiments. This finding supports the conclusions that graded activation patterns for future and completed actions in Experiment 1 and future actions in Experiment 2 were driven by activation states and not visual search time.

Experiment 4: Inserting Instead of Shifting the Go-Signal

Experiments 3 and 4 were designed to experimentally measure the influence of visual search and spatial confounds that may have been present during Experiments 1 and 2. During Experiment 3, while still shifting the go-signal position in space while limiting the preview window, we observed evidence of repetition priming and not visual search. However, in Experiments 1, 2, and 3, go-signals always cued letters in different spatial positions, so it is possible that some of our results are driven by spatial confounds. For example, RTs could be slower as a function of spatial position simply because the go-signal cue is more difficult to identify at more distal positions. Experiment 3 partly addressed this issue because cued letters were presented in the same spatial positions as Experiments 1 and 2, yet graded RTs were not observed. Experiment 4 addressed the spatial confound directly. Experiment 4 was the same as Experiment 1 except that the go-signal was always presented in Position 0, which was always the expected next letter in the sequence. To test the activation states of planned or completed responses, we inserted letters from the other positions in place of letter previously in Position 0.

Method

Subjects. Fifty subjects participated in Experiment 4. Seven subjects failed to complete the task. Five subjects were excluded from analysis for not meeting mean accuracy or RT criterion. The remaining 38 subjects (mean age = 36 years, *SD* = 10; 22 female, 14 male, two undefined) reported having been typing for 21 years (*SD* = 9 years), and started typing at 13 years old (*SD* = 4 years). Thirty-three were right-handed (four left-handed, one both), 16 reported that they had received some type of formal typing training during K-12education (21 indicated "no," one undefined), and 28 reported being able to touch type (10 indicated "no").

Apparatus and stimuli. Experiment 4 was the same Experiment 1, except the go-signal always cued Position 0. That is, the red letter always moved forward one spatial position in the sequence. However, when the go-signal was assigned to cue another position (−3, −2, −1, 1, 2, or 3), the letter from that position was inserted in place of the letter currently residing in Position 0.

Design and procedure. The design and procedure were the same as Experiment 1.

Results and Discussion

As with the previous experiments, RTs in each condition for each subject were submitted to an outlier elimination procedure (nonrecursive; Van Selst & Jolicoeur, 1994) that removed an average of 3% of observations from each condition. Additionally, an average of 32% of observations were removed from the analysis for trials meeting the confound criteria established in Experiment 1. Mean RTs for each participant at each go-signal position were then submitted to separate repeated measures ANOVAs, with go-signal position as the sole factor.

Mean RTs as a function of go-signal position are displayed in Figure 8A. The main effect of go-signal position was significant for RTs, $F(6, 198) = 78.4$, $MSE = 9{,}764$, $p < .001$, $\eta_p^2 = 0.70$.

RTs. Subjects were faster at Go-Signal Position 0 ($M = 512.4$, $SE = 18.6$) compared with Go-Signal Position +1 ($M = 916.8$, $SE = 34.0$), $t(33) = 17.64$, $p < .001$, and Go-Signal Position −1 ($M = 856.5$, $SE = 30.2$), $t(33) = -15.47$, $p < .001$. There was no

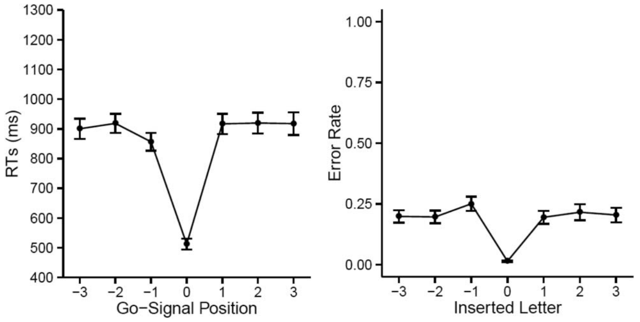

Figure 8. Mean reaction times (RTs; in ms) and error rates, with standard errors as a function of go-signal position for Experiment 4. The inserted letters from Positions −3 to +3 were always inserted into Go-Signal Position 0.

difference in RTs at Go-Signal Position +1 compared with Go-Signal Position +2 ($M = 919.6$, $SE = 35.3$), $t(33) = -0.11$, $p = .91$, or at Go-Signal Position +2 compared with Go-Signal Position +3 ($M = 917.6$, $SE = 38.0$), $t(33) = 0.74$, $p = .94$. Subjects were faster at Go-Signal Position −1 compared with Go-Signal Position −2 ($M = 918.5$, $SE = 31.7$), $t(33) = 4.44$, $p < .001$; however, there was no difference in RTs at Go-Signal Position −2 compared with Go-Signal Position −3 ($M = 900.4$, $SE = 34.2$), $t(33) = -0.78$, $p = .44$.

A post hoc linear contrast confirmed that RTs at Go-Signal Position −1 were not significantly different than RTs at the remaining completed and future go-signal positions, $t(231) = -1.65$, $p = .10$.

The results did not reproduce the same trends as observed in Experiments 1 and 2. Instead, RTs for completed and future responses are indicative of a narrow response range. The fastest response was always the expected letter, with completed and future responses showing little evidence of graded activation. RTs at Go-Signal Position −1 showed a modest priming benefit, and although RTs at Go-Signal Position −1 were faster than Go-Signal Position −2, linear contrasts revealed that there was no difference between Go-Signal Position −1 and the remaining completed and future go-signal positions.

Errors. Mean error rates as a function of go-signal position are displayed in Figure 8B. The main effect of go-signal position was significant for errors, $F(6, 198) = 13.49$, $MSE = 0.015$, $p < .001$, $\eta_p^2 = 0.29$. For the first time, error rates for completed and future actions were above 20%.

We did not see the same pattern observed in Experiments 1 and 2. It may be the case that despite the visual search control check in Experiment 3, spatial confounds may partly explain the results of Experiments 1 and 2. The results from the RT data appear to suggest that only the current response was most active. When responding to completed and future go-signal positions, with the exception of the recently executed response at Position −1, RTs were equally slow. One possible conclusion is that when keeping the position constant, the activation states for completed and future responses of a sequence may be activated along a narrow range. Another possibility is that the potency of the expected response at Go-Signal Position 0 may be hiding a wide activation range. This interpretation becomes more plausible when considering the perseveration data.

Interestingly, error rates were above 20% for future and completed actions, which is different from what was observed in Experiments 1 and 2. The analysis of perseveration errors suggests that when subjects committed an error they were most likely to type the expected letter at Go-Signal Position 0 as opposed to the inserted letter. Figure 9A shows the proportions of perseveration errors collapsed across all subjects, including those who did not make at least one error in each position. As with Experiments 1 and 2, an ANOVA analysis of perseveration errors was not possible because only a few subjects committed perseveration errors at every go-signal; however, according to independent samples t tests, there was no difference in perseveration errors between Positions +1 ($M = 0.97$, $SE = 0.02$) and −1 ($M = 0.93$, $SE = 0.04$), and Positions +2 ($M = 0.99$, $SE = 0.01$) and −2 ($M = 0.93$, $SE = 0.02$), $t(110) = -1.02$, $p = .31$, nor Positions ±2 and Positions +3 ($M = 0.96$, $SE = 0.04$) and −3 ($M = 0.90$, $SE = 0.04$), $t(110) = 1.41$, $p = .16$. Figure 9B shows the mean error rates for go-signal position after removing perseveration errors. The difference between error rates after removing perseveration errors was not significant, $F(6, 198) = 0.86$, $MSE = 0.0013$, $p = .86$, $\eta_p^2 = 0.02$. Error rates appear linear, with proportional range of errors falling within 0.01 to 0.02.

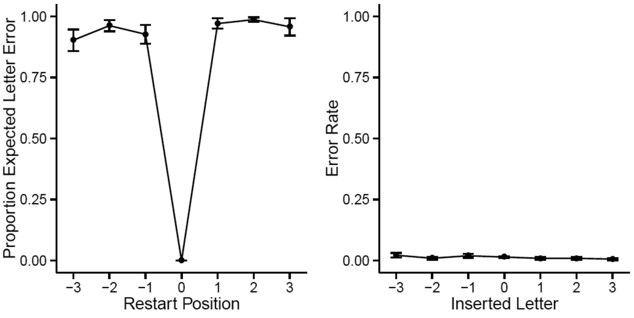

Figure 9. Mean proportion of perseveration errors and mean error rates with perseveration errors removed, with standard errors as a function of go-signal position for Experiment 4. A perseveration error occurs when the letter in the expected go-signal position (0) is typed in place of the cued letter.

Several models predict that position coding information can modulate the selection of other responses in a sequence. For example, Burgess and Hitch (1992) modeled position information as a moving window. This enabled multiple action elements to overlap one another, leading to serial-order errors, as well as graded activation states from completed and future responses. Oscillator models also take position codes into account, usually proposing the existence of a central oscillating timing mechanism (Brown et al., 2000; M. Treisman, Cook, Naish, & MacCrone, 1994). These models assume that item information is bound with its position. Because position never shifted in Experiment 4, RTs may have been high at all completed and future go-signal positions because the expected letter, and not the inserted letter, was tightly bound with the expected location. Subjects were forced to actively inhibit the planned response at the expected position in order to successfully type an unexpected letter inserted from a different location. Accordingly, when subjects committed errors, they were most likely to be perseveration errors, because the expected response was always the most active and the corresponding response was tightly bound with that position.

In summary, when typing normal English text, Experiment 1 revealed a wide, graded state of activation for completed and future responses consistent with competitive queuing models. When we removed their ability to plan in Experiment 2, we found evidence of deactivation for more distal completed responses, whereas future responses still showed a wide range of activation. Experiment 3 was designed to serve as a manipulation check for visual search confounds. We observed evidence for repetition priming for the most recent response, and flat RTs at the remaining go-signal positions. In Experiment 4, in order to address possible spatial confounds, we occasionally inserted a future or completed letter into Go-Signal Position 0, as opposed to shifted to a letter at a completed or future location. We found high perseveration errors and flat RTs at all go-signal positions except Position 0, suggesting that the potency of a specific response at the expected location may be hiding the wide activation range for completed and future responses.

One alternative explanation for findings from Experiment 4 was that the insertion of a completed or to-be-completed letter altered the word context. Specifically, inserting a letter may have had the effect of turning a normal string into a random letter or otherwise nonword string. Given previous research that has demonstrated that people are slower when typing random strings (Gentner et al., 1988; Shaffer & Hardwick, 1968), letter insertions from distal go-signal positions that disrupted the word context could have had the effect of slowing down processing time as a compensatory mechanism in order to produce accurate copy. We did not see this effect in Experiment 1, because changes in go-signal positions preserved the word context. One way to address this in the future would be to create a paradigm in which when an insertion occurs, the entire string is shifted with the insertion as well. If changing the word context was influencing our results from Experiment 4, then it is possible that preserving the word context while shifting distal responses into the expected location may produce results similar to what we observed in Experiment 1.

Our hypothesis was that activation states of completed and future responses may fall under a wide or narrow range of activation states, based on broad predictions from several models. A more satisfying way to make inferences about the activation states of completed and future responses would be to establish a baseline for responses that are not a part of the initial plan and compare RTs at go-signal positions for unplanned responses with RTs for planned responses. In Experiment 5, as subjects typed, occasionally they were shifted to a completed or future go-signal position. Sometimes the letter at that position was a letter they had previously typed or were planning to type. Sometimes the letter was novel, inserted from an array of letters that were not a part of their plan. This procedure could provide a more direct way of comparing responses in the queue with responses that are not a part of the queue.

Experiment 5: Measuring the Baseline

In the previous experiments, we used RTs as a proxy for measuring the activation states of completed and future actions. Our interpretation of the data was that differences in RTs at the different go-signal positions meant that the activation state of a letter at one position was either more or less active relative to the activation state of a letter at another position. One important issue that has not been addressed is the lack of a baseline for responses that are not elements of a current action sequence. If RTs for planned responses at future and completed go-signal positions are faster than RTs for unplanned responses, then those responses may be considered active relative to baseline. Conversely, if RTs for planned responses are greater or equal to baseline, then those activation states would be considered inhibited, or deactivated, relative to baseline responses.

The purpose of Experiment 5 was to establish a baseline RT at each go-signal position by occasionally having subjects type a letter that was not a part of their initial plan. Experiment five followed the general procedure of Experiment 1, with the exception that at each go-signal position the cued letter could be planned or unplanned. To accomplish this goal, we adopted a method from Crump and Logan (2010a; also see Masson, 1986), who divided the keyboard into a checkerboard pattern to create two sets of 13 letters, and two corresponding word lists in which each word was composed from letters from only one of the sets. The paragraph of words displayed to subjects involved one of the word lists, such that all of the letters were from one letter set. Critically, we manipulated whether or not the go-signal cued a completed or to-be-completed planned letter, or a randomly chosen unplanned letter from the unused letter set. This allowed us to establish a baseline for unplanned letters that we could compare to responses that were a part of the original planned sequence. Comparing RTs for planned responses to a baseline affords stronger inferences about the range of activation states of completed and future responses. If future planned responses are partially activated, then we would expect RTs for planned letters in those positions to be faster than baseline RTs for unplanned letters in those positions. Similarly, if completed responses are deactivated, then we would expect RTs for planned letters in those positions to be equivalent or even slower than RTs for unplanned letters in those positions. Alternatively, if the patterns of graded RTs across go-signal positions in Experiments 1 and 2 are driven primarily by proximity to the expected letter, and do not reflect response sequencing dynamics, then would expect no differences in RTs between planned and unplanned letters across go-signal positions.

We made one additional change from previous experiments to better approximate the conditions of normal continuous typing. Previous experiments used a randomly varying delay (100 to 300 ms) between each response and the next go-signal. As a result, subjects may have strategically adopted a more serial style of typing because they were forced to wait to execute each response. Experiment 5 removed the delay entirely, such that the next go-signal appeared simultaneously with a current response. The removal of the delay allowed typists to resume normal typing for consecutive keypresses at the expected go-signal location.

Method

Subjects. Fifty subjects participated in Experiment 5. Eight subjects failed to complete the task. Seven subjects were excluded from analysis for not meeting mean accuracy or RT criterion. The remaining 34 subjects (mean age = 35 years, *SD* = 8; 17 female, 16 male, one undefined) reported having been typing for 20 years (*SD* = 6 years), and started typing at 14 years old (*SD* = 5 years). Thirty subjects were right-handed (four left-handed, one both), 14 reported that they had received some type of formal typing training during K-12 education (22 indicated "no"), and 31 reported being able to touch-type (three indicated "no").

Apparatus and stimuli. Two arrays were created from the 26 letters of the alphabet (13 letters in each array). In order to control for possible typing confounds related to spatial letter location during the task, each letter array was constructed by creating two checkerboard patterns across the keyboard. Starting with the letter "Q," we placed each alternating letter in one of the two arrays (e.g., "Q" in Array 1, "W" in Array 2, "E" in Array 1). Six hundred forty-three 4- to 7-letter words were taken from a Scrabble website in which all of the letters of each word were either from Array 1 or 2. Importantly, letters from the first array were not used in any of the words from the second array, and vice versa.

Design. Prior to the experiment, a 232-word paragraph was constructed from words from one of the two arrays. Arrays were counterbalanced for each subject. As with the previous experiments, each go-signal response was cued when the to-be-typed letter changed from black to red. As opposed to the previous experiments, there was no jitter delay between go-signal changes. Subjects typed the first 10 letters, and afterward there was a 50% chance that the next letter would be the subsequent letter in the expected position, or would shift to a completed or future go-signal position. Additionally, after every go-signal position change, there was a 50% chance that a second algorithm swapped out the shifted letter with a letter from the unplanned array, thereby replacing that letter with a new letter that was not a part of the completed or future action sequence. For example, if a subject typed a letter in its expected position, and afterward the go-signal jumped three letter locations forward, there was a 50% chance that the letter at Go-Signal Position +3 was the same letter subjects were planning to type (e.g., for the word "PRAWN," subjects typed "P" and were shifted to "W") or was a letter inserted from the unplanned array (subjects typed "P" and were shifted to the location where the "W" was located, but "Q" is inserted instead). In addition to generating RTs for unplanned responses at completed and future go-signal positions, this method also allowed us to measure RTs for unplanned responses at Go-Signal Position 0. After every shift or insertion, the next four subsequent go-signal position changes always occurred for the expected letter at the expected position.

Procedure. The design and procedure were the same as Experiment 1.

Results and Discussion

As with the previous experiments, RTs at all go-signal positions for both planned and unplanned responses for each subject were submitted to an outlier elimination procedure (nonrecursive; Van Selst & Jolicoeur, 1994) that removed an average of 3% of observations. Additionally, an average of 22% of planned response trials and 5% of unplanned response trials were removed from the analysis meeting the confound criteria established in Experiment 1. Mean RTs for each participant at each go-signal position, for both planned and unplanned responses, were then submitted to separate repeated measures ANOVAs, with condition (planned vs. unplanned) and go-signal position as the within-subjects factors.

Mean RTs as a function of go-signal position for planned and unplanned responses are displayed in Figure 10A. There was a main effect of go-signal position, $F(6, 198) = 22.7$, $MSE = 30{,}261$, $p < .001$, $\eta_p^2 = 0.41$, condition, $F(1, 33) = 20.0$, $MSE = 32{,}804$, $p < .001$, $\eta_p^2 = 0.38$, and a go-signal by condition interaction, $F(6, 198) = 16.5$, $MSE = 23{,}419$, $p < .001$, $\eta_p^2 = 0.33$.

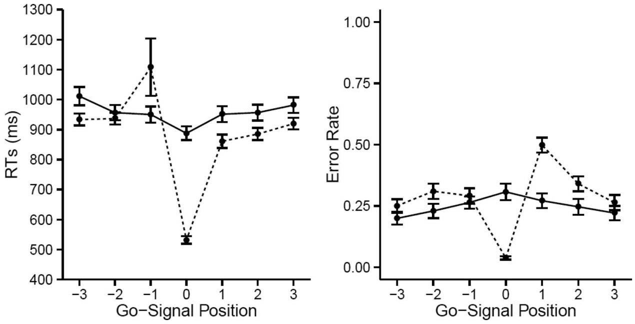

Figure 10. Mean reaction times (RTs; in ms) and error rates, with standard errors as a function of go-signal position for Experiment 5 for planned (dashed lines) and unplanned responses. The inserted letters from Positions −3 to +3 were always inserted into Go-Signal Position 0.

RTs. For planned responses, subjects were faster at Go-Signal Position 0 ($M = 532.0$, $SE = 12.8$) compared with Go-Signal Position +1 ($M = 861.1$, $SE = 22.0$), $t(33) = -18.06$, $p < .001$, and Go-Signal Position −1 ($M = 1{,}107.7$, $SE = 95.6$), $t(33) = 6.28$, $p < .001$. There was no difference in RTs at Go-Signal Position +1 compared with Go-Signal Position +2 ($M = 885.2$, $SE = 20.2$), $t(33) = -1.41$, $p = .17$, or at Go-Signal Position +2 compared with Go-Signal Position +3 ($M = 919.7$, $SE = 19.5$), $t(33) = -1.97$, $p = .06$. RTs were faster at Go-Signal Position +1 compared with Go-Signal Position +3, $t(33) = 3.52$, $p = .001$. There was no difference in RTs at Go-Signal Position −1 compared with Go-Signal Position −2 ($M = 936.8$, $SE = 19.5$), $t(33) = -1.88$, $p = .07$, or at Go-Signal Position −2 compared with Go-Signal Position −3 ($M = 933.4$, $SE = 19.6$), $t(33) = -0.20$, $p = .84$.

For unplanned responses, subjects were faster at Go-Signal Position 0 ($M = 887.7$, $SE = 22.7$) compared with Go-Signal Position +1 ($M = 951.3$, $SE = 26.4$), $t(33) = -4.31$, $p < .001$, and Go-Signal Position −1 ($M = 950.3$, $SE = 26.9$), $t(33) = 3.73$, $p < .001$. There was no difference in RTs at Go-Signal Position +1 compared with Go-Signal Position +2 ($M = 956.7$, $SE = 26.3$), $t(33) = -0.29$, $p = .77$, at Go-Signal Position +2 compared with Go-Signal Position +3 ($M = 981.5$, $SE = 26.2$), $t(33) = -1.43$, $p = .16$, or at Go-Signal Position +1 compared with Go-Signal Position +3, $t(33) = -1.84$, $p = .08$. There was no difference in RTs at Go-Signal Position −1 compared with Go-Signal Position −2 ($M = 956.4$, $SE = 25.7$), $t(33) = 0.36$, $p = .72$; however, RTs were faster at Go-Signal Position −2 compared with Go-Signal Position −3 ($M = 1{,}011.4$, $SE = 30.7$), $t(33) = 2.09$, $p = .04$.

We compared RTs between planned and unplanned responses at each go-signal position. RTs were faster for planned compared with unplanned responses at Go-Signal Position −3, $t(33) = 2.74$, $p = .01$. There was no difference at Go-Signal Positions −2, $t(33) = 0.87$, $p = .39$, and −1, $t(33) = -1.83$, $p = .08$. RTs were faster for planned compared with unplanned responses at Position 0, $t(33) = 18.77$, $p < .001$, Position +1, $t(33) = 4.20$, $p < .001$, Position +2, $t(33) = 3.85$, $p < .001$, and Position +3, $t(33) = 3.57$, $p < .001$.

The RTs for planned responses were similar to what we observed in Experiments 1 and 2. RTs for future responses are indicative of a wide response range consistent with models of parallel activation, whereas completed responses suggest a narrow range. As with the previous experiments, the fastest response was always the expected letter, with future responses showing a graded state of activation and more distal completed responses showing deactivation. RTs at Go-Signal Position −1 were likely slow because of an artifact of the task. In the previous experiments, there was a short jitter between changes in go-signal position. In Experiment 5, as soon as subjects responded, the next go-signal position was cued without delay. When subjects were forced to respond to the −1 position during the planned condition, the letter would have remained red, likely making the manipulation more difficult to detect.

Conversely, RTs for unplanned responses do not show a range of graded activation states. Subjects were faster at responding to Position 0, and a little bit slower when responding to Position −3, but for the most part, RTs for unplanned responses display a linear trend compared with planned responses across go-signal positions, thereby providing a stable baseline for comparison between activation states of planned versus unplanned responses. The fact that RTs for unplanned responses did not mirror RTs for planned responses from Experiments 1, 2, and 5 supports our previous conclusion that RTs were not a function of visual search. If the results from previous experiments were driven by the time it took to locate and respond to the shifted letter, then we would have expected to see RTs that showed a V pattern.

Importantly, when comparing RTs for planned versus unplanned responses, we found evidence of a wide range of activation states for future responses and a narrow activation range for completed responses. At Go-Signal Positions 0 through +3, RTs for planned responses were always faster than unplanned responses. This is consistent with predictions of parallel activation suggesting that all responses are activated simultaneously and that individual elements compete with one another for selection. RTs at Go-Signal Positions −1 and −2 were not significantly different than baseline, suggesting these responses are rapidly deactivated after completion; however, there appears to be some residual activation for responses at Position −3 compared with baseline. It may be the case that the more current completed responses are rapidly deactivated so as to avoid typing those letters in error, but more distal responses may still retain some level of activation.

Errors. Mean error rates as a function of go-signal position for planned and unplanned responses are displayed in Figure 10B. There was a main effect of go-signal position, $F(6, 198) = 26.5$, $MSE = 0.0111$, $p < .001$, $\eta_p^2 = 0.45$, condition, $F(1, 33) = 11.8$, $MSE = 0.0131$, $p < .001$, $\eta_p^2 = 0.26$, and a Go-Signal × Condition interaction, $F(6, 198) = 30.7$, $MSE = 0.0125$, $p < .001$, $\eta_p^2 = 0.48$.

Error rates were robust across go-signal position for planned and unplanned responses. Figure 11A shows the proportions of perseveration errors collapsed across all subjects, including those who did not make at least one error in each position. According to independent samples *t* tests, perseveration errors were greater for unplanned responses between Position +1 ($M = 0.95$, $SE = 0.02$) and −1 ($M = 0.81$, $SE = 0.04$) and Positions +2 ($M = 0.83$, $SE = 0.04$) and −2 ($M = 0.74$, $SE = 0.05$), $t(125) = 2.34$, $p = .02$, but not between Positions ±2 and Positions +3 ($M = 0.79$, $SE = 0.05$) and −3 ($M = 0.79$, $SE = 0.05$), $t(125) = -0.12$, $p = .91$. For planned responses, perseveration errors were greater between Position +1 ($M = 0.96$, $SE = 0.01$) and −1 ($M = 0.98$, $SE = 0.01$) and Positions +2 ($M = 0.82$, $SE = 0.04$) and −2 ($M = 0.87$, $SE = 0.03$), $t(127) = 4.30$, $p < .001$, but not between Positions ±2 and Positions +3 ($M = 0.84$, $SE = 0.05$) and −3 ($M = 0.75$, $SE = 0.05$), $t(127) = 1.13$, $p = .26$. Finally, perseveration errors were robust for unplanned responses at Go-Signal Position 0 ($M = 0.88$, $SE = 0.04$). Figure 11B shows the mean error rates for go-signal position for planned and unplanned actions after removing perseveration errors. Error rates varied from 0.01 to 0.09 at all go-signal positions for both planned and unplanned responses.

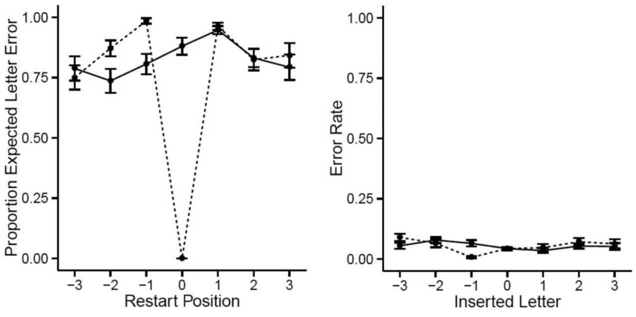

Figure 11. Mean proportion of perseveration errors and mean error rates, with perseveration errors removed with standard errors as a function of go-signal position for Experiment 5 for planned (dashed lines) and unplanned responses. A perseveration error occurs when the letter in the expected go-signal position (0) is typed in place of the cued letter.

General Discussion

The main purpose of the study was to validate a novel behavioral measure, so the validity of interpretations needs to be considered in detail. We broadly classified models of sequencing processes by whether they assume a wide or narrow dynamic range of response set activation. Our empirical goal was to validate a measure of the momentary activation states for any given response in a response set. Across five experiments, subjects copied text when prompted by a go-signal that usually cued the next letter in the sequence, but sometimes cued recently completed or to-be-completed letters. The RTs to restart typing following the go-signal were taken as an index of the underlying activation state of the cued action.

Experiments 1 (words) and 2 (random letter strings) showed a pattern of graded RTs across future go-signal position ($0 < 1 < 2 = 3$), consistent with parallel activation of actions in a planned sequence and a wide dynamic range. RTs in Experiment 1 also showed a similar graded pattern across past go-signal positions ($0 < -1 < -2 = 3$), consistent with gradual deactivation of completed responses; however, outside of a priming benefit observed at Go-Signal Position −1, completed RTs in Experiment 2 showed evidence consistent with a wide dynamic range. We further investigated whether the graded activation of RTs across go-signal positions was driven by spatial confounds. Experiment 3 restricted preview to the cued letter, which eliminated parallel activation of future responses, but maintained the presentation of cued letters in different spatial positions. The results showed only evidence of repetition priming when the go-signal cued the previous response. Experiment 4 removed the spatial position confound by inserting letters from distal positions into the expected next-letter position. The results showed evidence consistent with a narrow dynamic range, suggesting an important role for spatial codes. Finally, in Experiment 5, we replicated our procedure from Experiment 1, and also provided a baseline for comparing planned and unplanned responses at the different go-signal positions. We observed evidence of parallel activation for future responses consistent with a wide dynamic range, and rapid deactivation of completed responses. We turn to extended analyses of the evidence for a wide dynamic range of response set activation, as well as how our experiments speak to the sequencing processes operating in the narrow range.

Evidence for Parallel Activation and Wide Dynamic Range

We interpret the symmetrical pattern of graded RTs across past and future letter positions in Experiment 1 and future responses in Experiment 2 as evidence for graded activation states for each response in a planned sequence. An alternative view is that the pattern of RTs reflects the time taken to visually search for the go-signal. Experiment 3 partly argues against this view because letters appeared in the same spatial positions as previous experiments, but RTs did not vary as a function of position. However, the absence of graded RTs here could be explained by a parallel search process that quickly identified all letters in the absence of any distractors (A. M. Treisman & Gelade, 1980). At the same time, even when full preview was available, it is possible that visual search for the go-signal could occur in parallel because the cued letter was a color based feature singleton (which are known to pop out), and cued letters were always within close spatial proximity to the current letter. However, we saw no evidence of a pop-out effect. Furthermore, tests of linearity for future responses in Experiments 1 and 2 showed that nonlinear functions provided a better fit for our data. Finally, unplanned responses in Experiment 5 did not show a symmetrical V pattern that we observed in the other experiments, suggesting that our overall findings were not driven by visual search times.

The nonlinear pattern of RTs across future go-signal positions is consistent with competitive queueing models of action sequencing. For example, the Rumelhart and Norman (1982) model assumes that all responses are activated in parallel, and that each response inhibits all remaining responses (see Figure 1B). As a result, inhibition is applied multiplicatively across positions in the sequence, which would translate to a graded nonlinear pattern of activation strengths across positions.

The absence of a similar nonlinear pattern of RTs for future go-signal positions in Experiment 4 is consistent with multiple interpretations. Some readers may be convinced that removing the spatial confound and showing an absence of graded RTs across positions shows that our measure is not tapping response activation states. On the other hand, spatial position codes may be strongly linked to the momentary activation states of particular responses. As a result, Experiment 4 may not index the activation states of distal letters, but could instead measure the ensuing response competition between the inserted and planned letter.

To test the possibility that position codes dynamically modulate activation states, we looked at the proportion of perseveration errors across positions for Experiments 1, 2, 4, and 5. If perseveration errors were simply a result of subjects typing the expected letter instead of the shifted or inserted letter, then it is reasonable to assume that perseveration errors would be consistent across completed and future go-signal positions; however, Experiments 1 and 5 revealed that perseveration errors were highest at positions that were the most proximal to Go-Signal Position 0. This may have occurred because the response for Position 0 was always the most activated. In fact, the further away the shifted response was from Go-Signal Position 0, the less likely subjects were to commit perseveration errors. In Experiment 2, we observed that perseveration errors occurred at go-signal positions in which the completed and future responses may have been most competitive with the expected response. In all cases, perseveration errors were high at the fastest go-signal positions, suggesting that letters in these positions were more active in relation to distal go-signal positions. However, in Experiment 4, we found high rates of perseveration errors and slow RTs at all completed and future go-signal positons. It may be the case that when inserting a letter, as opposed to shifting to a new location, the letter and its corresponding position code may have been bound in a way that led to slow RTs and high perseveration errors. Alternatively, as addressed in the discussion for Experiment 4, it is also possible that the flat RT pattern we observed was because inserting a letter from a distal go-signal position disrupted the word context, which in turn led to slower RTs.

Sequencing Operations in the Narrow Range

We have focused primarily on whether sequencing models assume that multiple responses are planned in parallel or in series, and testing these ideas by measuring the width of the dynamic range for response activation during sequencing. Our data show some evidence that future responses have graded activation strengths, and that there is a wide dynamic range in typing. At the same time, much of the “action,” so to speak, occurs in the narrow range. For example, models ascribe two important sequencing functions to the completion of an action: deactivating the completed response and triggering of the next response.

In the introduction, we suggested that several sequencing models make different general predictions about the activation states of completed and future responses. For example, Panel A of Figure 2 shows a flat line indicating complete deactivation for previous responses, consistent with predictions from Rumelhart and Norman (1982). We found supporting evidence for this prediction. In Experiments 2 and 4, we observed a priming benefit at Go-Signal Position −1; however, RTs at Go-Signal Positions −2 and −3 were equally slow, suggesting completed responses may be rapidly deactivated. Importantly, results from Experiment 5 suggest that completed actions are rapidly deactivated, particularly when compared with unplanned responses. Averbeck et al. (2002) found that deactivation for each completed line segment gradually reduced over time within a window of 300 to 600 ms. Because we used RTs at completed and future go-signals as a proxy for activation states, we cannot make any claims about the time it took for a completed response to deactivate; however, RTs at completed go-signal positions are within the window of the deactivation gradients observed by Averbeck and colleagues.

Narrow-range models assume that actions are triggered by the completion of a previous response, or perhaps an associated hierarchical control unit. Wide-range models assume that an upcoming action is partially activated before the response is completed, and becomes fully activated after inhibition is released by the deactivation of a completed response. Experiments 1, 2, 4, and 5 all showed overwhelming evidence that the fastest response always occurred when the go-signal cued the expected next letter in the sequence (i.e., Position 0).

Input–Output Buffering

Normal typing is accomplished using a complex input–output buffering process in which typists are thought to take in segments of to-be-typed text while executing keystrokes for previously perceived letters that are stored in a buffer. As a consequence, typists tend to look *n* letters ahead or behind the letter they are typing. For example, previous research using eye tracking during typing has shown that participants’ eye-hand span is roughly −2 to +7 letter positions away from the current letter being typed (see Inhoff & Gordon, 1997). One possible confound with our interpretation that RTs at unexpected go-signal positions represent the activation states of completed and to-be-completed responses in the buffer is that RTs at unexpected go-signal positions may be driven by failures of input or buffering processes prior to serial output. Taking the Rumelhart and Norman (1982) model as an example, our behavior measures could be influenced by input-level processing of the to-be-typed text. For example, if a participant failed to scan ahead to letter $n+3$ and the go-signal subsequently shifted to that position, then we would expect slower RTs for that response, because that letter failed to be inputted into the buffer. Similarly, we would also expect uniformly faster RTs for letters in the buffer that are activated in parallel, but not yet weighted for serial output. The present methods do not isolate the specific contributions from these earlier stages, and resolving this issue is an important avenue for further work.

At the same time, we suggest that participants were inputting and buffering letters in accordance with normal typing behavior. First, when subjects made errors, they commonly made perseveration errors, typing the expected next letter rather than the letter indicated by the go-signal. Some perseveration errors likely reflect an input problem with detecting the go-signal, presumably because subjects were actively previewing upcoming text. Similarly, perseveration errors also indicate successful input and buffering of the upcoming letter. Second, the RT differences between planned and unplanned future responses in Experiment 5 suggest that participants were successfully inputting and buffering responses because RTs were faster for planned than unplanned responses. Notably, planned responses showed a gradient consistent with competitive queuing models (Estes, 1972; Rumelhart & Norman, 1982), whereas unplanned responses were linear, providing further support that our pattern of RTs are driven by serial output processes. Finally, go-signal shifts occurred anywhere from one to three locations away from the expected target positions. Inhoff and Gordon (1997) reported that the optimum fixation point was about three letters away from the expected location. Our manipulation fit squarely within the optimum range that participants should have been previewing.

Conclusions

The major aim of this article was to provide a new behavioral measure of the dynamic range of activation of responses during action sequencing. We identified serial and parallel models of action sequencing that predict wide or narrow dynamic response ranges for planned actions. We used RT and error rate data during a novel task that forced subjects to sometimes type an unplanned letter at different or expected locations as a proxy for the activation states of completed, current, and to-be-completed responses. Overall, our data showed that future actions are activated across a wide dynamic range, consistent with competitive queuing model predictions (e.g., Rumelhart & Norman, 1982). In general, subjects were fastest for the letter in the expected location, and progressively slower for more distal letters from the expected location. The graded level of activation we observed suggests that responses were activated in parallel and inhibited in series, with earlier responses in the sequence being more active than later responses. Additionally, when controlling for go-signal timing in Experiment 5, completed responses were rapidly deactivated, and planned responses were faster than unplanned responses that served as a baseline for activation states of unbuffered responses.

An overarching goal of our method was to convince typists to engage in normal typing behavior and then occasionally test their performance for letters in unexpected go-signal positions. We then used these measures of performance as an index of the activation state of the probed response. Of course, in the process of introducing unexpected go-signal changes, we inevitably disrupt normal typing and perhaps induce strategies for accommodating to the new task demands. For example, a participant might decide not to preview and plan future responses as normal and simply wait for upcoming go-signals before responding. Experiment 5 represented our best attempt to induce normal typing behavior by removing the delays between go-signals. In general, it is difficult to use behavioral measures to index the activation state of completed or to-be-completed actions without disturbing their dynamics with the measurement probe. It is noteworthy that our behavioral findings corroborate the single-unit recording data in monkeys observed by Averbeck and colleagues (2002). They observed that prior to monkeys drawing geometric shapes, populations of neurons that fired for each individual line segment displayed a graded state of activation, consistent with that line's location in the serial order. Furthermore, firing rates for completed lines reduced to baseline within 500 ms. We are optimistic that future work on these issues will shed light on the interaction between timing and dynamic range, the role of position codes in response scheduling, and further differentiate between input and output processes in the buffer driving action activation dynamics.

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