

Nazbanou Nozari^{a,b*} and Christopher R. Hepner^a

^aDepartment of Neurology, Johns Hopkins University, Baltimore, USA; ^bDepartment of Cognitive Science, Johns Hopkins University, Baltimore, USA

Correspondence should be addressed to:

Nazbanou Nozari, MD, PhD

Address: 1629 Thames Street, Suite 350, Baltimore, MD 21231, USA

Phone: 443-287-1712

Pre-Review Only

In Nozari and Hepner (this issue), we proposed a theoretical framework for reconciling two seemingly irreconcilable theories of lexical selection: competitive vs. non-competitive selection. By superposing a decision framework (signal detection theory) onto the distributions of conflict derived from the core dynamics of mapping semantic features to lexical representations, we argued that a flexible selection criterion could accommodate patterns predicted by both competitive and non-competitive models of lexical selection. Five excellent commentaries posed

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In memory of Albert Costa, who always sparked a good debate.

In Nozari and Hepner (this issue), we proposed a theoretical framework for reconciling two seemingly irreconcilable theories of lexical selection: competitive vs. non-competitive selection. This approach views the word production system as comprising two separate (but related) models: a) a model of the internal dynamics of mapping one layer of representation to another, a process that leads to the *activation* of representations, and b) a model of decision-making based on the information generated by the first system, a process that leads to *selection* (see Nozari, 2019, for neuropsychological evidence of the separation of activation and selection processes). In our framework, we have deliberately avoided modelling the internal dynamics of production because excellent models of these dynamics already exist (e.g., Foygel & Dell, 2000; Rapp & Goldrick, 2000). While we encourage combining them with a model of decision-making, this has not been the purpose of the current proposal. Instead, our goal here has been to show that the dynamics of activation (as implemented by such models) naturally generate information (i.e., conflict) that is useful for decision-making processes in the production system. Examples of such decision-making processes are those which determine when to mark a response as an error (Hanley, Cortis, Budd, & Nozari, 2016; Nozari, Dell, & Schwartz, 2011) or, as Nozari and Hepner (this issue) have argued to be a natural extension, when to delay selection in order to decrease the chance of an error in the first place.

In five insightful commentaries, Anders and Alario (this issue; A&A), Costa (this issue), Mahon and Navarrete (this issue; M&N), Melinger and Abdel Rahman (this issue; M&A), and Oppenheim and Balatsou (this issue; O&B) provided a wide range of comments on the utility,

feasibility, and relevance of the framework, as well as suggestions for future applications. In the following two sections, we first tackle the issues of utility and feasibility. Many of the comments by M&A, M&N, and O&B are addressed here. The third section deals specifically with the comments of A&A on the link between evidence accumulation (EA) models and the current proposal. The fourth section addresses the remaining comments. We end by highlighting some of the unanswered questions encouraged by the current framework.

Two of the commentaries (M&A and M&N) questioned the usefulness of the proposed framework, for exactly opposite reasons. M&A see the problem of lexical selection as already solved in favor of the competitive view, while M&N view competitive selection as altogether illusory, an artifact of specific experimental paradigms. In a recent review of the behavioral, neuroimaging, and EEG evidence of co-activation of multiple representations during production, we evaluated both of these claims (Nozari & Pinet, under review). In keeping with the claims of M&A, the empirical evidence for interference in word production is robust. Paradigm-specific idiosyncrasies cited as creating illusory interference (e.g., Navarrete, Del Prato, Peressotti, & Mahon, 2014) have been addressed with further empirical studies (e.g., Belke, Shao, & Meyer, 2017), and manipulation of semantic distance has shown that closer semantic relationships induce greater interference (Rose, Aristei, Melinger, & Abdel Rahman, 2019). There is, thus, little doubt, given the current state of the empirical evidence, that semantic similarity can, and often does, induce real interference in production.

Robustness of interference, however, does not automatically translate into competitive lexical selection. It has been shown that such interference can in fact be generated by other

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3 mechanisms, such as incremental learning (Oppenheim, 2018; Oppenheim, Dell, & Schwartz,
4 2010), without appealing to competitive selection. Similarly, ERP differences between
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6 semantically related and unrelated words during picture naming, which have often been taken as
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8 evidence for competitive lexical selection, might find an alternative—and potentially more
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10 powerful—explanation in the dynamics of spreading activation (see Nozari & Pinet, under
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12 review). It is true that, to date, non-competitive mechanisms like incremental learning have not
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14 been applied to findings from the PWI paradigm, whereas such findings can be easily
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16 accommodated using a competitive selection mechanism (Roelofs, 2018). How much weight
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18 should be given to findings from the PWI paradigm, which entails processes other than those
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20 routinely engaged in word production (e.g., reading or auditory processing of a distractor), is
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22 currently a topic of debate (see Oppenheim & Balatsou, this issue, vs. Roelofs, 2018).
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30 To summarize, empirical evidence of interference arising from a non-strategic process is
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32 strong. However, in most cases, this interference can be explained by both competitive and non-
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34 competitive models of lexical selection. There are two ways out of this: 1) To continue adding
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36 to the very large body of behavioral and neural evidence, and interpreting them within the
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38 existing theoretical frameworks. It seems to us that this approach has reached the limits of its
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40 explanatory potential. 2) To entertain the possibility of a framework within which both selection
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42 mechanisms are possible. This framework, signal detection theory (SDT), has been immensely
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44 successful in testing the predictions of fixed threshold vs. flexible criterion models in a wide
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46 range of perceptual and cognitive tasks (see Wixted, in press, for an outstanding review of the
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48 history of SDT), and can speak to *why* performance looks competitive in one case and non-
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50 competitive in another. The purpose of Nozari and Hepner (this issue) was to advocate the
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52 adoption of this approach for understanding lexical selection.
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6 Two of the commentaries (M&A and A&A) raised concerns about the functionality of the
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8 proposed framework. Before we address these concerns, we feel that potential ambiguity
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10 relating to our use of the term “task goals” must be resolved. To make things clearer, we will
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12 draw a distinction between a *task demand* and a *performance goal*. By *task demand*, we mean
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14 the activity that must be performed. Using M&A’s example, naming all of the pictures and
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16 naming a subset based on a certain rule would constitute activities with different *task demands*
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18 (within the same PWI paradigm). By *performance goal*, we mean the prioritization of either
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20 speed or accuracy. Thus in M&A’s example, there are *two* different task demands (name all of
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22 the pictures vs. name a subset) but only *one* performance goal.
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28 Are the *task demand* and the *performance goal* truly separable parameters? Yes. These
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30 two factors can be manipulated orthogonally. One could, for example, hold the task constant
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32 (e.g., name all of the pictures) while using different instructions to manipulate performance goals
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34 (“Respond as quickly as possible.” vs. “Make sure you do not make a mistake.”). Conversely,
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36 one could hold the performance goal constant (prioritize speed) while changing the task (name
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38 all of the pictures vs. name only the subset of pictures that matches rule X). The criterion would
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40 only be expected to change in the latter example, when the *performance goal* changes, and not
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42 when the *task demand* changes. In keeping with this prediction, Aristei and Abdel Rahman
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44 (2013) did not observe a change in the pattern of performance in their experiment because only
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46 the *task demand*, and not the *performance goal*, had changed.
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52 Model fitting provides empirical evidence for the independence of these two parameters.
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54 Figure 1a shows data from 60 participants in a recent word typing study by our lab. Participants
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56 heard a word and typed it under time pressure without immediate visual feedback. After each
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trial, they were asked whether they had made an error or not. A signal detection model was fitted to each individual's data in order to estimate two parameters: $A\beta$ and c . The $A\beta$ parameter

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6 The application of SDT and EA models to word production indeed shares a common goal: both
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8 models highlight the importance of viewing word production as a goal-oriented task with a
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10 decision-making component (see Nozari, 2018, for elaboration of this view). However, A&A go
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12 further to claim that our proposed approach “reduce[s] [neural network model] components to a
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14 framework of accumulation (of inverse conflict)”, and that DDMs will emerge as superior
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16 models because they are “a standard above current fitting procedures”. This section evaluates
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18 these claims.
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23 Recall that the purpose of the proposed framework has been to demonstrate that two
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25 seemingly opposing theories (competitive vs. non-competitive selection) can be accommodated
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27 within a unified model. This claim does not itself require data fitting. The next step is to
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29 determine which model is the correct model of word production: purely competitive, purely non-
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31 competitive, or a hybrid (the current proposal). This is what must be verified with empirical
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33 data. The current framework makes it clear that the key issue is whether there is a fixed
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35 threshold or a flexible criterion. With regard to model fitting, neither EA nor SDT models are
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37 immune to the challenges inherent in working with production data (e.g., dealing with
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39 omissions). Those challenges aside, both DDMs and SDT models can be fitted to individual data
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41 (see example above), can be discriminated between fixed threshold and flexible criterion models,
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43 and can model trial-by-trial shifts of the criterion (e.g., Brown & Steyvers, 2005). There are thus
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45 no inherent shortcomings in the SDT framework as far as model fitting is concerned. In light of
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47 this, we will compare the suitability of the EA models advocated by A&A over the current
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49 proposal for the purpose at hand.
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56 EA and SDT are closely related frameworks for modelling decision-making behavior, but
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they have one prominent difference. The former models the process of evidence accumulation

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models to more complex tasks successfully, but this requires merging them with other types of models like NNMs (e.g., the LCA model; Usher & McClelland, 2001).

When simple EA models are applied to cognitively complex processes like word production, non-trivial problems arise. The RT on each production trial is the product of a complex, non-linear process in a system with cascading and interactivity (see Dell, Nozari, & Oppenheim, 2014, for a review of the evidence for these). An EA model must unpack all of this information from the RTs in a meaningful way. This is a problem that does not exist for the type of quick, low-level judgments usually modelled using EA (Ratcliff et al., 2016). In addition, assumptions that may be valid for forced-choice tasks in simple serial systems, like positing a “non-decision” component which is independent of the “decision” components, are questionable for a complex non-serial process like word production. For example, EA models of word production have included motor processing in the “non-decision” time after a word has been selected (e.g., Anders et al., 2015; Anders, Riès, van Maanen, & Alario, 2017). However, Baese-Berk and Goldrick (2009) found longer voice onset times for the initial consonants of words that had a minimal pair with a voiced initial consonant, showing that articulatory-motor processes are not independent of the prior stages of processing.

These and similar problems lead to results which are sometimes sharply at odds with other types of models (e.g., NNMs). For example, the finding of *higher* accumulation rates in individuals with brain damage compared to healthy controls (Anders et al., 2017) is the opposite of what NNMs of damaged systems predict (e.g., Dell et al., 1997; Dell, Schwartz, Nozari, Faseyitan, & Branch Coslett, 2013; Nozari & Dell, 2013). If we accept, based on their ability to fit RTs, that EA models are superior to other model types, we must also accept that damaged systems transmit information *faster*. This would in turn require an entirely new cognitive theory

of damage that, in addition to the new findings, would also account for all of the data that was

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3 *1) The scope of a decision-making framework.* We continue to emphasize that the dynamics of
4 spreading activation in a semantic-lexical space are a big part of lexical retrieval. These reflect
5 the speaker's knowledge structure; i.e., which features connect to each other to form a concept,
6 which concepts are linked to each other through their features, which lexical items are linked to
7 which features and to each other, etc. No generalized decision-making framework, including
8 SDT, can or should replace specialized cognitive models designed to capture the dynamics of
9 semantic-to-lexical mapping. Indeed, when seeking to understand the differences in behavior
10 across tasks with different materials/demands, these dynamics should be the first line of
11 investigation. Strong motivation for this approach comes from studies of concept processing,
12 which have shown that the pattern of neural activity for a concept differs depending on task
13 demands and context (e.g., Hargreaves, White, Pexman, Pittman, & Goodyear, 2012; Musz &
14 Thompson-Schill, 2015). It is thus quite reasonable, for example, to expect verbs and nouns to
15 be activated differently depending on which one must be produced in a task (M&N). There is,
16 however, a longstanding tradition of separating language processing from other goal-oriented
17 tasks. Current models of word production that include syntactic processing do not treat task
18 demands as a key factor in shaping the activation in semantic-lexical space. They assume that
19 nouns and verbs are activated equally up to the point at which selection occurs (Gordon & Dell,
20 2003). We suggest that this assumption may need to be revisited in the light of the evidence that
21 task demands introduce early constraints on processing often way before decision points.
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48 The scope of a decision-making framework, in contrast, is limited to explaining how
49 selection decisions are optimized based on performance goals (i.e., prioritizing either speed or
50 accuracy). For example, explaining a change from producing lots of quick commission errors to
51 lots of omission errors in the same picture naming task within the same individual with aphasia
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3 described in the first point above), they are correct in stating that a criterion may change from
4 trial to trial. Indeed, if language production is subject to the same kind of decision-making
5 process as other cognitive systems like visual processing and memory, as both we and others
6 have argued (Anders et al., 2015, 2017; Nozari, 2018; Nozari & Hepner, this issue), the selection
7 criterion is highly likely to vary from trial to trial (e.g., Benjamin, Diaz, & Wee, 2009). These
8 adjustments would be perfectly compatible with an incremental learning process, examples of
9 which have been found in other production processes (e.g., Breining, Nozari, & Rapp, 2018;
10 Oppenheim et al., 2010; Warker & Dell, 2006).
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26 Current behavioral data suggest that similarity-induced interference in picture naming is more
27 than an illusion. The corresponding neural data show that the production system is indeed
28 sensitive to the co-activation of similar representations. Neither of these findings, however,
29 provides conclusive evidence for competitive selection models. We suggest investigating
30 whether a system with a flexible criterion, which has been shown to provide a better explanation
31 for performance in other cognitive domains, could also be more successful in explaining
32 selection in word production. By no means does this imply that current models of word
33 production should be replaced with a decision-making model. Rather, a decision-making
34 framework can be superposed on the dynamics of such models. If a flexible-criterion model can
35 provide a better account for the data than a fixed-threshold model, then the issue of competitive
36 vs. non-competitive selection gives way to new questions: “How often and under what
37 circumstances does the selection criterion change?”, “How do differences in learning affect
38 criterion shifts?”, or “What conditions impair the adjustment of the criterion based on
39 performance goals?”. This may, in turn, allow us to differentiate between problems stemming
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3 from impaired transmission of information between layers of representations, and those resulting
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5 from setting a maladaptive criterion for selection in individuals with aphasia.
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11 This work was supported in part by the Therapeutic Cognitive Neuroscience Fund endowed to
12 the Cognitive Neurology division of the Neurology Department at Johns Hopkins University.
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14 We would like to thank Rasha Abdel Rahman, Evangelia Balatsou, Albert Costa, Alissa
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16 Melinger, Brad Mahon, Eduardo Navarrete, and Gary Oppenheim for their thoughtful
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18 commentaries. We would also like to thank John Wixted for his insightful comments about the
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