Lexical Selection by Competition in Word Production: Evidence from New Paradigms

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There is significant debate in language production concerning whether or not lexical selection relies on competition among candidate words. Increases in picture naming latency in the face of manipulations of alternative lexical (picture-word interference) [8] or conceptual activation (semantic blocking) [3] have been taken to reflect time needed to resolve competition for lexical selection. However, the same effects are also explained by non-competitive post-lexical monitoring accounts [4]; the controversy may reflect the difficulty of interpreting latency as a test of competition (A) more generally, or (B) specifically under complex task manipulations [cf 4,5]. To address (A), we complement naming latency with an investigation of a more direct measure of selection—the likelihood of dominant name production (name agreement--NA). To address (B) we depart from prior research by studying picture naming without semantic manipulation. Instead, we expand our focus beyond the dominant name for a picture. If word candidates compete during lexical selection, properties of the next strongest (**secondary**) picture name should influence competition and thus naming behavior. By contrast, previous research has investigated how the dominant name for a picture is influenced by properties of *that name alone*, including NA [10,11], dominant name frequency or Age of Acquisition (***AoA***) [7,9]**,** and the strength of image-name agreement (***IA***) [10]. If selection is non-competitive, then the secondary name properties should be less relevant than dominant name properties, but if selection involves competition, then secondary name properties should affect NA and latency.

We examined predictors of picture naming in a study using pictures with a wide distribution of dominant NA (167 Native English participants, naming 20 target images with 120 filler pictures and words, yielding 3151 observations). We assembled existing norms and collected new data on dominant and secondary picture names: AoA, conceptual familiarity, imageability [9]; NA; and new IA ratings. ***IA Norms:*** Target pictures [11] appeared on screen with two previously identified dominant and secondary names, along with sliders for rating them, Figure 1). Ten catch trials with one implausible name were included to verify task compliance. Participants (Amazon mTurk, n = 67, native English speakers) provided IA ratings by moving the onscreen sliders for both picture names. Ratings for the dominant name were a significantly better predictor of dominant naming rates compared to pre-existing IA norms [10], $\chi^2 = 2.79$, $p < .01$. The correlation between dominant and secondary ratings was negative ($r = -.44$), but not overwhelmingly so, because both alternative names were often rated highly.

Results. Alternative mixed effects models were fit to dominant naming rates (***NA***: 1 = dominant name, 0 = other) and onset latency (ms). Models comprised unique combinations of either dominant or secondary name properties [7] (Table 1). ***NA:*** Comparing models for overall model fit (lowest AIC) revealed secondary IA and AoA as better predictors of dominant naming (whereas a model with both dominant predictors ranked 4^{th}; Figure 2). The stronger fit of a model with secondary predictors *in place of dominant predictors*, suggests secondary names are central to the likelihood of dominant naming, and supports competition in lexical selection. ***Naming latency:*** The best fit model comprised only dominant name predictors. We therefore see no evidence for secondary name variables affecting latency to produce the dominant name. This is more consistent with a non-competitive account of latency data in lexical selection.

Conclusions. By considering both secondary and dominant name properties, data from a single-task picture-naming study new effects emerged, associated with secondary names. These results are consistent with theories of selection without claims about latency [1]. With respect to accounts that selection is non-competitive [4,5], or circumstantially competitive [6], these data suggest that naming *latency* might not be competitive, but not the conclusion that selection is also non-competitive. Best-fit models for latency and name agreement were markedly different. Future work should further investigate the relationship between NA and latency for informing theory about lexical selection.

		best fit model	
Abbr.	**Description**	**Naming**	**Latency**
AoA	Age of Acquisition [9]	S > D	D > S
IA	Image agreement [*]	S > D	D > S
NA	Name Agreement [*]	-	D > S
Fam	Conceptual Familiarity [9]	D	D
Ivar	Image Variability [9]	D	D

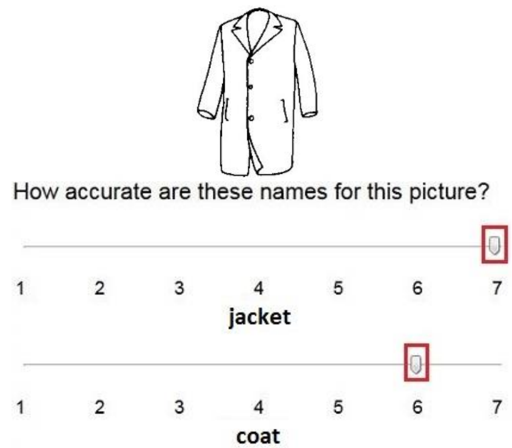

Table 1 (left). Predictors in best-fit models of naming and latency data. Models of each (Secondary vs Dominant) permutation of target predictors (AoA, IA, NA) were compared (4 models for naming, 8 for latency). Legend: - = not modeled; D = dominant predictor only; D < S (S < D) best fit between dominant and secondary predictor; [#] = source; [*] = collected here.

Figure 1 (right). Norming trial: Participants provided IA ratings for dominant and secondary names, where 7 = perfectly accurate, 1 = completely misleading (red added for clarity). Sample and order of pictures, order of dominant and secondary names on screen were counterbalanced.

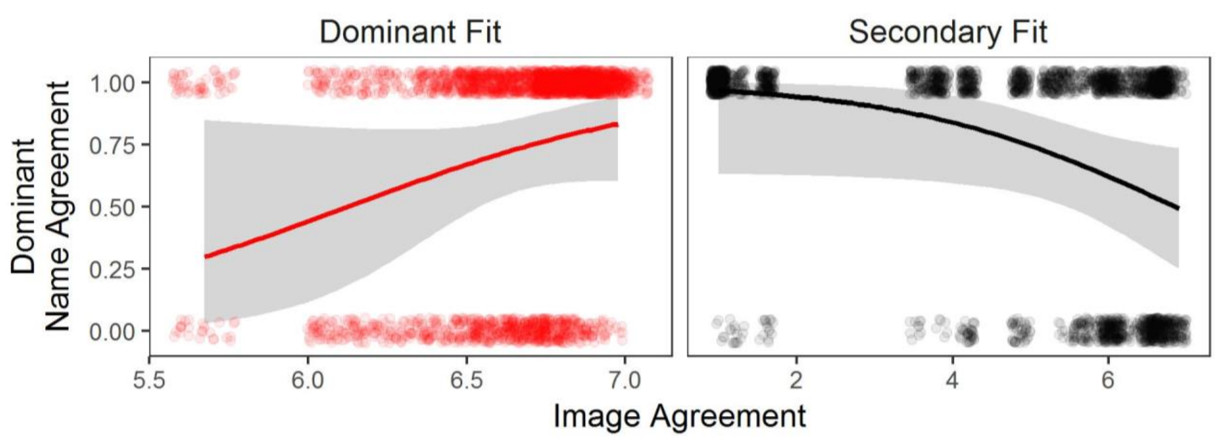

Figure 2. Likelihood of saying the dominant name, as predicted by dominant (**left**) vs secondary (**right**) image agreement. Secondary image agreement improves overall model fit. (One item removed from graph, only: underwear/diaper.)

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