

# Predictive memory activation attenuates similarity-based interference in verb-final languages

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## Abstract

Cue-based retrieval theories of sentence comprehension assume that syntactically related words (e.g., the subject and the verb) are identified and linked together through a content-addressable search in memory, using retrieval cues such as *subject* and *animate*. A key prediction is similarity-based interference: When multiple nouns in memory match retrieval cues at the verb, it becomes difficult to retrieve the target subject noun, causing a slowdown in processing time at the verb. Similarity-based interference is consistently observed in reading studies from English, furnishing strong evidence for cue-based retrieval theories. However, in verb-final languages such as German and Hindi, evidence is equivocal. The classical cue-based retrieval models fail to explain interference effect patterns observed in verb-final languages. Data demand a new theory that can explain interference effects in verb-final as well as verb-medial languages. We explore the predictive memory activation mechanism: the pre-verbal nouns stored in memory strongly preactivate the upcoming verb phrase, which can override the cost of retrieval interference in verb-final languages. We implement this mechanism within a cue-based retrieval architecture. We show that the predictive memory activation model can account for interference effects observed in verb-final as well as verb-medial languages. Bayes factor analysis revealed strong evidence in favor of the predictive memory activation model against the cue-based retrieval model. Our modeling results have an important theoretical implication: Dependency completion is driven by top-down predictive activation and bottom-up cue-based retrieval processes.

**Keywords:** cue-based retrieval; similarity-based interference; prediction; working memory

## Introduction

Comprehending a sentence requires us to resolve dependencies between the verb and its arguments. For instance, to comprehend the sentence *the boy kicked the basket*, we must figure out *who* did the action of kicking and *what* was being kicked. This dependency completion process is critical for sentence comprehension. What are the cognitive processes that underlie real-time dependency completion? A well-established theory is the cue-based retrieval theory, which assumes that dependency completion between a verb and its arguments is driven by a content-addressable search in memory (McElree, 2000; Van Dyke, 2007; Van Dyke & Lewis, 2003; Van Dyke & McElree, 2011). When the verb is encountered, a search is triggered in memory for the target subject noun using retrieval cues such as *subject* and *animate*; the noun that matches these retrieval cues is retrieved for dependency completion.

However, sometimes non-subject nouns in memory match the same retrieval cues, causing difficulty in retrieving the

subject noun. This retrieval difficulty arising from multiple nouns matching the retrieval cues is called similarity-based interference. Similarity-based interference is one of the key predictions of cue-based retrieval theories (Lewis & Vasishth, 2005). For example, consider the sentences (1a-1b).

1. (a) **the resident**<sup>+animate</sup> who was living near the dangerous neighbour<sup>+animate</sup> **was complaining**<sub>[animate]</sub> about ...
- (b) **the resident**<sup>+animate</sup> who was living near the dangerous warehouse<sup>-animate</sup> **was complaining**<sub>[animate]</sub> about ...

In sentence (1a), the comprehender faces difficulty in identifying the target subject noun at the verb *was complaining* due to shared semantic feature *+animate* with the distractor noun *neighbour* as compared to sentence (1b) where the distractor *warehouse* does not share the *+animate* feature. This predicted retrieval difficulty due to the presence of semantically similar nouns in memory is called semantic interference (Van Dyke, 2007). Thus, the model predicts a slowdown in reading times at the verb in sentences like (1a) compared to sentences like (1b). This semantic interference predicted by the model is consistently observed in reading and eye-tracking studies in English.

2. (a) **the resident**<sup>+subject</sup> who said that the neighbour<sup>+subject</sup> was dangerous **was complaining**<sub>[subject]</sub> about ...
- (b) **the resident**<sup>+subject</sup> who was living near the dangerous neighbour<sup>-subject</sup> **was complaining**<sub>[subject]</sub> about ...

Similarly, in sentence (2a), as per cue-based retrieval account, it is difficult to identify and retrieve the target subject noun *the resident* because it shares syntactic features *+subject* with the distractor *neighbour*, in contrast to sentence (2b) where the distractor noun does not share any syntactic feature with the subject noun. Thus, the model predicts syntactic interference: The difficulty in retrieving the target subject noun when non-subject nouns in memory match the syntactic cue *[subject]* at the verb (Van Dyke, 2007; Van Dyke & Lewis, 2003). A slowdown is predicted in reading times at the verb in (2a) compared to condition (2b).

Both syntactic and semantic interference are robustly observed in reading (and eye-tracking) studies from English (Arnett & Wagers, 2017; Van Dyke, 2007; Van Dyke & Lewis, 2003). However, when it comes to verb-final languages such as German and Hindi, there is no clear evidence

for similarity-based interference. For example, in a German eye-tracking study, Mertzen et al. (2023) found syntactic interference but no evidence for semantic interference. However, in a large-scale replication of the Mertzen et al. (2023) study, Schoknecht et al. (2025) found no evidence for syntactic interference and weak evidence for semantic interference in German. In a reading study on Hindi, Husain et al. (2025) found no evidence for similarity-based interference due to multiple nouns that shared case marking features.

Mertzen et al. (2023) proposed an explanation for the absence of semantic interference and presence of syntactic interference in their study: German participants rely strongly on syntactic cues and give lesser weightage to semantic cues during dependency completion. This differential cue weighting in German can be attributed to the rich morphosyntactic case marking (Slioussar, 2018). However, the cue weighting explanation does not hold because in the direct replication of the Mertzen et al. (2023) study, no syntactic interference was observed by Schoknecht et al. (2025).

Another possible explanation was proposed by Husain et al. (2025). They propose the *prediction facilitation hypothesis*: The pre-verbal nouns predict the properties of the upcoming verb phrase in memory, which facilitates processing when the verb is encountered. Since predictability might be a stronger and more relied upon strategy in verb-final languages, this prediction facilitation in verb-final languages is strong enough to cancel the retrieval interference cost at the verb. This is a theoretically important proposal because top-down prediction has been argued to play an important role in processing verb-final languages (Vasishth & Lewis, 2006; Vasishth et al., 2010; Husain et al., 2014) and there have been attempts to integrate prediction and working memory in a single set of assumptions (Futrell et al., 2020).

We implement the predictability proposal within the cue-based retrieval model of Lewis and Vasishth (2005) such that when pre-verbal nouns are encoded, they probabilistically preactivate the upcoming verb phrase in memory through a spreading activation mechanism. We call it *the predictive memory activation model*. The model assumes that intervening items between the subject and the verb can preactivate the upcoming verb phrase, causing a facilitation in processing at the verb. This preactivation-facilitation can override the retrieval interference effect. The model further assumes that predictability is a stronger and more relied upon strategy in verb-final languages compared to verb-medial languages due to the robustness of rich case-marker cues and frequent exposure to head-final structures.

We generate predictions from the existing cue-based retrieval model and our proposed predictive memory activation model for syntactic and semantic interference in English, German, and Hindi. We test model predictions using published studies on English and German. To evaluate model predictions in Hindi, we conduct a new self-paced reading experiment on similarity-based interference in Hindi. We quantify evidence for the predictive memory activation model com-

pared to the classic cue-based retrieval model using data from existing reading studies on English and German and our new study on Hindi.

We find that our Hindi study shows no evidence for syntactic interference and weak evidence for semantic interference. The results are totally consistent with the large-scale German study by Schoknecht et al. (2025), but completely go against the predictions of the cue-based retrieval model.

Interestingly, the predictive memory activation model could account for the qualitative pattern of interference effects observed in verb-final as well as verb-medial languages. The Bayes factor analysis shows strong evidence in favor of the predictive memory activation model against the cue-based retrieval model, given data from English, German, and Hindi.

Next, we describe the assumptions and predictions of the cue-based retrieval model and the predictive memory activation model one-by-one. After that, we evaluate the models using data from five reading studies on English, German, and Hindi.

## The cue-based retrieval model

The cue-based retrieval model assumes that:

- (1) Dependency completion between the subject and the verb is driven by a cue-based retrieval process using retrieval cues such as *subject* and *animate*.
- (2) All nouns that match retrieval cues receive a certain amount of activation, and a noun with the highest activation gets retrieved for dependency completion.
- (3) The retrieval time is determined by the activation level of the retrieved item.

Consider example sentences in Figure 1. In sentence (3a), when the reader encounters the verb *complained*, a search is triggered in the memory for the target subject noun using retrieval cues [*subject*, *animate*]. The subject noun *the attorney* receives only half of the activation from each retrieval cue because the distractor noun *the visitor* also matches both the retrieval cues. While in (3b), the target subject noun receives half of the activation through the subject cue but full activation through the animate cue because the distractor does not match the animate cue. Thus, the activation of the target subject noun is overall lower in sentence (3a) compared to (3b). Consequently, the model would predict slower retrieval time in condition (3a) compared to condition (3b).

The total activation  $A_i$  of a noun  $i$  is determined by its baseline activation  $B_i$  and activation received through the retrieval process  $\sum_{j=1}^n W_j S_{ij}$ .

$$A_i = B_i + \sum_{j=1}^n W_j S_{ij} + \epsilon_n \quad (1)$$

where the baseline activation  $B_i$  depends on the history of past retrievals of the item  $i$ ;  $\epsilon_n$  is the activation noise in  $n_{th}$  trial such that  $\epsilon_n \sim Normal(0, \sigma)$ . The activation received by a noun  $\sum_{j=1}^n W_j S_{ij}$  is the weighted sum of the strength of

association between item  $i$  and cue  $j$ , where  $W_j$  is the relative weight of cue  $j$ .

The strength of association  $S_{ij}$  is determined by the *fan effect*: As the number of nouns that match the retrieval cue  $j$  increases, the associative strength between  $i$  and  $j$  decreases. The associative strength  $S_{i,j}$  can be given by the difference between maximum associative strength  $MAS$  (fixed at 1) and  $\ln(fan_j)$ , where  $fan_j$  is the number of items that match the retrieval cue  $j$ .

$$S_{ij} = MAS - \ln(fan_j) \quad (2)$$

The item that holds the highest total activation in the trial gets retrieved for dependency completion. The retrieval time at the verb is the exponential function of the activation level of the retrieved chunk  $i$

$$RT_i = Fe^{-A_i} \quad (3)$$

where  $F$  is called the latency factor, which represents the overall reading speed of a participant. It may include time taken for lexical access, motor response, and other non-decision times. The latency factor is a free parameter in the model.

### Predictions of the cue-based retrieval model

We generate prior predictions from the cue-based retrieval model for interference effects in the verb-final as well as verb-medial languages. We choose the following prior on the latency factor  $F$  to avoid unreasonably fast and unreasonably slow reading times (see Yadav et al., 2023)<sup>1</sup>:

$$F \sim Normal_{lb=0.05}(0.45, 0.05) \quad (4)$$

Figure 2 shows prior predictions for the interference effects from the cue-based retrieval model in verb-final (e.g., Hindi) and verb-medial (e.g., English) languages. The model predicts syntactic and semantic interference in both verb-final and verb-medial languages, in the range of [6,45] milliseconds. The model is unlikely to account for the full range of data because in verb-final languages, the syntactic and semantic interference effects are rarely observed.

### The predictive memory activation model

The predictive memory activation model assumes that:

- (1) Dependency completion between the subject and the verb is driven by a cue-based retrieval process (see the previous section).
- (2) The pre-verbal nouns may preactivate the upcoming verb phrase in memory through a spreading activation mechanism; the source preactivation is higher in verb-final languages compared to verb-medial languages.

<sup>1</sup>The prior we have chosen here deviates from typical prior assumptions about the latency factor in cue-based retrieval modeling literature. This is because we have implemented a simplified version of the model. The prior chosen here is based on the criteria that the model should not generate unreasonably fast ( $< 50\text{ms}$ ) and unreasonably slow ( $> 1500\text{ms}$ ) reading times.

- (3) The lexical access and encoding time of the verb chunk is determined by the degree of its pre-activation in memory.

Drawing from the cue-based retrieval model, the predictive memory activation model assumes that each item in memory matching a retrieval cue receives a certain amount of activation.

$$A_{i,t} = B_i + \sum_{j=1}^n W_j S_{ij} + \epsilon_n \quad (5)$$

However, the activation of an item can also increase due to preactivations. The activation of the upcoming verb phrase  $k$  in memory increases due to spreading pre-activation from each pre-verbal noun that associates with the verb  $k$ :

$$A_{k,t} = ((B_k + G_p S_{1,k})e^{-(t_2-t_1)} + G_p S_{2,k})e^{-(t_3-t_2)} + \dots \quad (6)$$

where  $B_k$  is the baseline activation of the verb phrase  $k$ ;  $G_p S_{1,k}$  is the amount of pre-activation spread from the pre-verbal noun 1 to the verb phrase  $k$ . Here,  $G_p$  is the source preactivation parameter,  $(t_2 - t_1)$  is the time elapsed between the noun 1 and the noun 2 and  $(t_3 - t_2)$  is the time elapsed between the noun 2 and the noun 3. The associative strength  $S_{1,k}$  between noun 1 and verb  $k$  is determined by their history of co-retrievals, which can be captured using head-dependent mutual information between the two; the value of this parameter can be estimated from a corpus or using a language model.

The model further assumes that source preactivation  $G_p$  used for preactivation spread is stronger in verb-final languages compared to verb-medial languages. This assumption operationalizes the proposal that top-down prediction is possibly more robust and relied upon in rich case-marking, verb-final languages compared to verb-medial languages (Vasishth et al., 2010; Husain et al., 2014). We assume that the value of parameter  $G_p$  is higher than 0.5 in verb-final languages and lower than 0.25 in verb-medial languages.

The reading time at the verb  $k$  in the  $n^{\text{th}}$  trial is determined by the time taken to lexically access and encode the verb chunk  $k$  and the time taken to retrieve the target argument noun  $i$ :

$$T_{k,n} = Fe^{-A_{k,t}} + Fe^{-A_i} \quad (7)$$

where  $F$  is the latency factor parameter, which reflects overall reading speed of the comprehender.

### Predictions of the predictive memory activation model

We generate prior predictions from model for interference constructions in verb-final as well as verb-medial languages. We choose the same prior on the latency factor  $F$  as in the cue-based retrieval model.

The predictive memory activation model has another free parameter, the source preactivation  $G_p$ . As discussed earlier, we assume higher source preactivation (stronger predictability) in verb-final languages compared to verb-medial

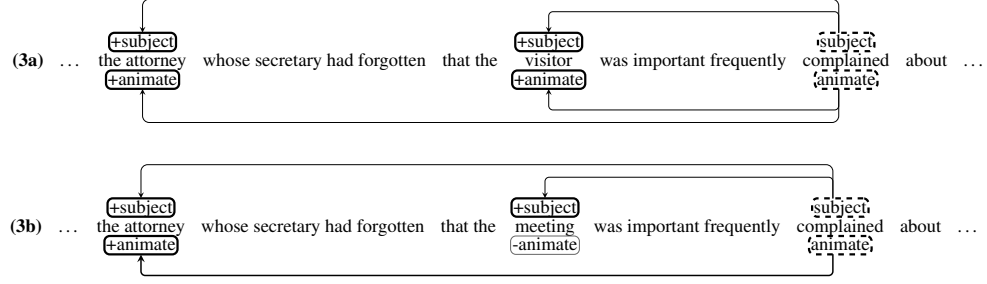


Figure 1: Activation received by the nouns based on cue-feature match, with a thick arrow denoting more activation spreading compared to a thin arrow. A **dashed** box represents a retrieval cue, a **thick** box represents a feature that matches a retrieval cue, and a **thin** box represents a feature that does not match a retrieval cue.

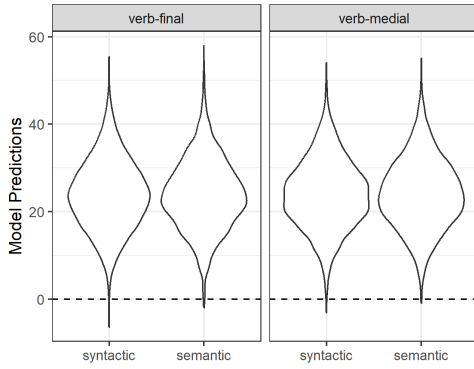


Figure 2: Prior predictions of the cue-based retrieval model. The y-axis shows the interference effect predicted by the model in milliseconds.

languages. We choose the following priors on  $G_p$  for verb-medial and verb-final languages:

$$G_p^{\text{verb-medial}} \sim \text{Normal}_{lb=0.05, ub=0.5}(0.15, 0.05) \quad (8)$$

$$G_p^{\text{verb-final}} \sim \text{Normal}_{lb=0.5, ub=1}(0.75, 0.05) \quad (9)$$

Figure 3 shows prior predictions of the predictive memory activation model in verb-final and verb-medial languages. The model predicts syntactic and semantic interference in verb-medial languages. Interestingly, in the verb-final languages, the model predicts a weak semantic interference and a weak anti-syntactic interference effect (i.e., an effect opposite to the syntactic interference effect). The model is promising because in verb-final languages, the semantic interference effects are always weak and syntactic interference often shows up in the opposite direction.

### Model predictions vs. observed data

We assess whether the predictive memory activation model can qualitatively account for the observed interference effects in five studies on English, German, and Hindi. For English

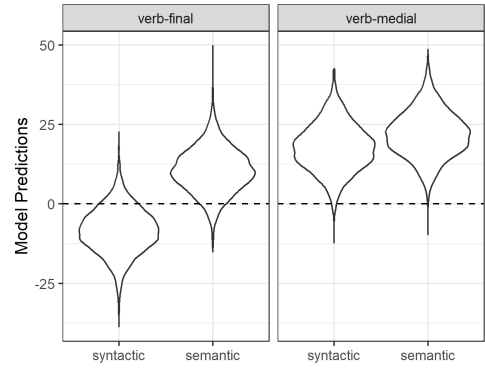


Figure 3: Prior predictions of the predictive memory activation model.

data, we use the Van Dyke (2007) and Mertzen et al. (2023) studies. For German data, we use the Mertzen et al. (2023) and Schoknecht et al. (2025) studies. For Hindi, there is no published study on syntactic and semantic interference. We conduct a new experiment (N=62) to test syntactic and semantic interference in Hindi using similar constructions as in Van Dyke (2007). We fit a hierarchical Bayesian regression model to estimate the posterior distribution of the syntactic and semantic interference.

We compare the predictions of the cue-based retrieval model and the predictive activation model against observed effects from five studies on English, German, and Hindi.

Figure 4 shows predictions of the cue-based retrieval model against the observed interference effects from the five studies. The model predictions for semantic interference effects are consistent with most of the studies. But the model fails to account for the syntactic interference effect observed across languages. The model can explain the syntactic interference in English but not in German and Hindi.

Figure 5 shows predictions of the predictive memory activation model against the observed interference effects. The model predictions are consistent with observed syntactic and semantic interference effects across languages. The model qualitatively captures the syntactic as well semantic interfer-

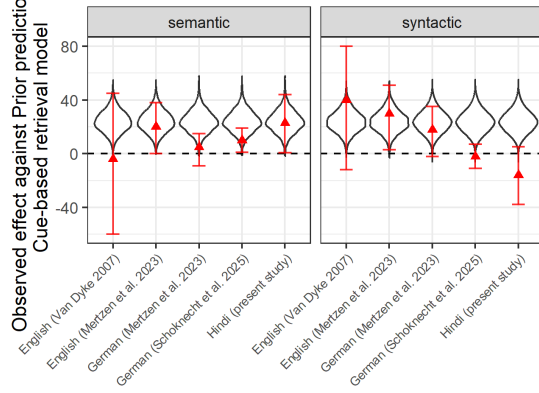


Figure 4: The prior predictions generated by the cue-based retrieval model are shown as violin plots. The observed interference effect in a study is shown as a red triangle, along with its 95% credible interval shown as error bars.

ence effect observed in most of the studies. The model succeeds because the distractor noun in the syntactic interference condition preactivates the verb phrase, causing a facilitation in processing that overrides the retrieval interference cost in verb-final languages.

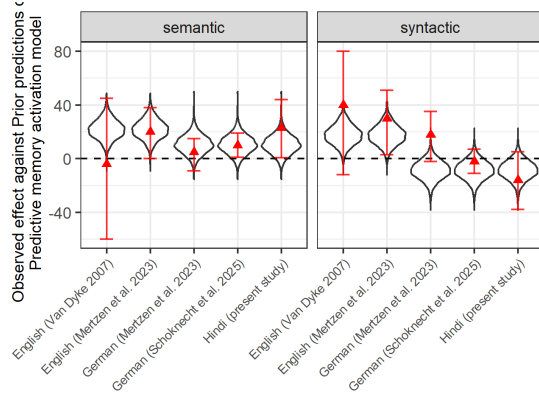


Figure 5: The prior predictions of the predictive memory activation model are shown as violin plots against the observed interference effect shown as red triangles and error bars.

### Model comparison

We quantify evidence for the predictive memory activation model against the existing cue-based retrieval model of Lewis and Vasishth (2005) using interference effect data from four published studies on English and German and a new experiment on Hindi.

We use Bayes factors to quantify evidence for the model given the data. The Bayes factor in favor of  $\mathcal{M}1$  over  $\mathcal{M}2$  is computed by taking the ratio of the marginal likelihoods of the two models. The Bayes factor for  $\mathcal{M}1$  over  $\mathcal{M}2$  repre-

sents the extent to which Model  $\mathcal{M}1$  is more likely than  $\mathcal{M}2$  given the data. We interpret a Bayes factor larger than 10 as strong evidence for a model. We quantify Bayes factors in favor of the predictive memory activation model against the cue-based retrieval model.

Figure 6 shows Bayes factors in favor of the predictive memory activation model given data from five studies on similarity-based interference. We find strong evidence (Bayes factors  $> 10$ ) for the predictive memory activation model under different prior assumptions on the source preactivation parameter in verb-final languages. The results suggest that the predictive memory activation model can explain the observed interference effects better than the existing cue-based retrieval model, across typologically different languages.

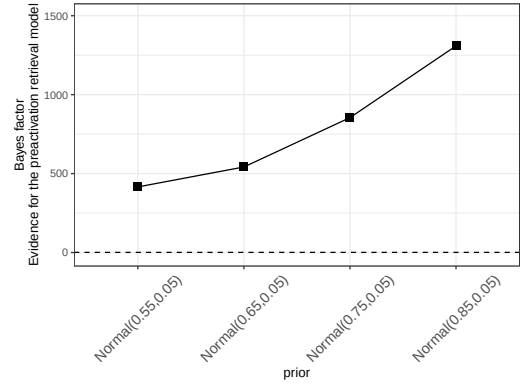


Figure 6: The Bayes factors showing evidence in favor of the predictive memory activation model under different prior assumptions on predictability strength in verb-final languages.

### Discussion

We investigated whether a predictive memory activation mechanism can account for the similarity-based interference patterns in both verb-final and verb-medial languages. We evaluate the model against the classic cue-based retrieval model (Lewis & Vasishth, 2005) using four published studies from English and German and a new experiment we conducted on Hindi.

We find that (a) the predictive memory activation can account for the qualitative pattern of syntactic and semantic interference effects observed across languages; and (b) there is strong evidence that the predictive memory activation model performs better than a retrieval-only model at explaining the interference effect across five studies.

Given considerable empirical support for robust predictability in verb-final languages from (anti-)locality and structural forgetting studies (Konieczny, 2000; Vasishth et al., 2010; Husain et al., 2014), it is reasonable to assume that a predictive memory activation is an important component of the underlying sentence comprehension process. The comprehension system can adapt to language-specific properties; for example, verb-final language comprehenders are exposed

to a rich case-marking system and a high frequency of head-final structures. It could be the case that verb-final language speakers develop predictability as a stronger and more relied upon strategy in verb-final languages compared to verb-medial languages. When we implement this assumption in a cue-based retrieval architecture, we are able to account for the full range of interference effects across languages. The predictive memory activation mechanism is a plausible explanation for observed similarity-based interference in resolving subject-verb dependencies.

A key observation with regard to similarity-based interference effects is the difference in the observed pattern across verb-final (e.g., German, Hindi) and verb-medial (e.g., English) languages. The verb-final languages make use of information from all the pre-verbal nouns (subject, object) to predict verb while this advantage is missing in verb-medial languages. Due to relatively poor top-down prediction in verb-medial languages, dependency completion in these languages is predominantly driven by a bottom-up retrieval process. Consequently, similarity-based interference is more pronounced in these languages.

The proposed model has some limitations. It assumes that the representation of pre-verbal linguistic material remains intact in memory; however, this assumption is challenged by considerable empirical support for the representation distortion hypothesis: The nouns stored in memory probabilistically distort to a non-veridical representation (Yadav et al., 2023). There are outstanding questions regarding the predictive memory activation mechanism, such as what kind of pre-verbal material leads to stronger preactivation of the verb. We plan to take these up in future work.

Our modeling work reveals theoretically important insights into the underlying sentence comprehension process: the real-time dependency completion is driven by a cue-based retrieval process that incorporates a predictive memory activation mechanism. This is the first quantitative evaluation of the predictability proposal for explaining the syntactic and semantic interference effects observed across languages. Our work contributes to understanding how working memory constraints and predictability interact to determine dependency completion in real-time.

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