To Words and Beyond: Probing Large Language Models for Sentence-Level Psycholinguistic Norms of Memorability and Reading Times

Anonymous ACL submission

Abstract

Large Language Models (LLMs) have recently been shown to produce estimates of psycholinguistic norms, such as valence, arousal, or concreteness, for words and multiword expressions, that correlate with human judgments. These estimates are obtained by prompting an LLM, in zero-shot fashion, with a question similar to those used in human studies. Meanwhile, for other norms such as lexical decision time or age of acquisition, LLMs require supervised fine-tuning to obtain results that align with ground-truth values. In this paper, we extend those works to the additional features of sentence memorability and reading times, which involve the relationship between multiple words in a sentence-level context. Our results show that via fine-tuning, models can provide estimates that correlate with human-derived norms, demonstrating that LLMs contain useful information about sentence-level features. At the same time, our results show very mixed zero-shot performance, providing further evidence that care is needed when using LLM-prompting as a proxy for human cognitive measures.

1 Introduction

How much useful information do Large Language Models (LLMs) contain about human psycholinguistic features? Prior work indicates that LLMs are able to predict word-level features such as concreteness or valence (Trott, 2024), age of acquisition (Sendín et al., 2025), and lexical decision times (Martínez et al., 2025) as well as for multi-word expressions (Martínez et al., 2024), (Brysbaert et al., 2024). One method of testing for the presence of useful psycholinguistically relevant information within LLMs is to simply prompt LLMs by asking a psycholinguistic query directly in zero-shot fashion. However, some evidence points to a lack of **introspection** in LLMs — their responses to prompts are not necessarily consistent with their latent knowledge that can be accessed in other ways, such as by inspecting token log-probabilities rather than directly prompting (Song et al., 2025; Hu and Levy, 2023). Fine-tuning language models based on small amounts of supervised data provides a way to better capitalize upon the rich learned model representations of pre-trained models. For example, Conde et al. (2025b) fine-tuned Llama 3 models to predict English familiarity ratings, achieving Pearson's correlation improvements of up to 0.3 over zero-shot baselines.

The approach of prompting an LLM to provide psycholinguistic norms differs from approaches which directly predict psycholinguistic features based on theoretically motivated, interpretable features. For example, surprisal theory states that human processing difficulty during reading is related to the predictability of words in context (Hale, 2001; Smith and Levy, 2013; Levy, 2008). For the domain of word memorability, Tuckute et al. (2025) used the theoretically motivated predictors of number of meanings and number of synonyms to predict the memorability of words, while Clark et al. (2026) used the distinctiveness of a sentence's Sentence-BERT semantic embedding (Reimers and Gurevych, 2019), as a theoretically motivated, zero-shot, sentence-level predictor of sentence memorability (among other features such as average word memorability and average word frequency). Table 1 lays out a comparison of these three different approaches. In our view, these methods address different questions, and thereby form a complementary set of approaches that collectively shed light on the functioning of LLMs and their alignment with human cognition.

Probing for psycholinguistic features exists as part of a broader paradigm of using artificial intelligence models to study and simulate human cognition (Frank and Goodman, 2025; Hagendorff et al., 2024; Binz et al., 2025). The use of LLM-prompting in cognitive science has also raised ques-

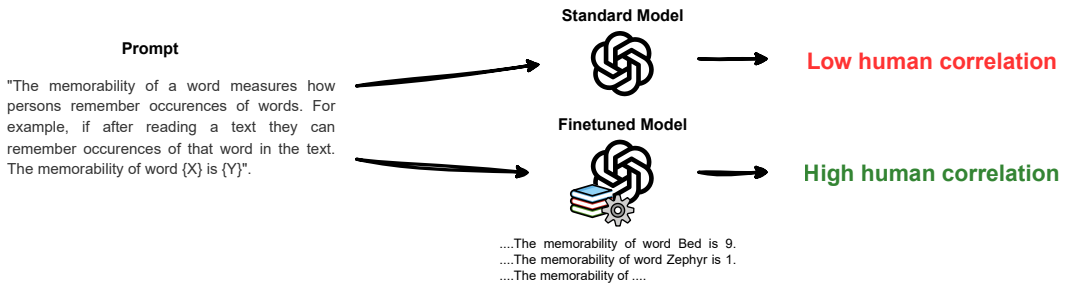

Figure 1: Overview of our approach, contrasting zero-shot prompting with fine-tuning on small supervised datasets for predicting psycholinguistic norms.

tions both about the best methodologies for eliciting predictions, as well as calls for caution regarding using LLM outputs as a substitute for human data (Gao et al., 2025; Dentella et al., 2023). Within this landscape, it is crucial to understand how well LLM outputs actually align with varied psycholinguistic features, whether and how this alignment can be improved, and whether the paradigm of LLM-prompting can be extended to sentence-level, and not just word-level, features.

In this paper, we go beyond existing work studying word-level psycholinguistic features in LLMs, and explore whether LLMs can generate predictions for norms which require processing at the sentence level. Specifically, we systematically compare zero-shot vs. fine-tuned predictions from LLMs to psycholinguistic behavioral norms, across the domains of memorability and reading times.

Our contributions are as follows:

1. We demonstrate that for memorability (both word and sentence-level), zero-shot prompting yields predictions that are uncorrelated with empirical norms. Meanwhile, for reading times, zero-shot prompting yields predictions that do correlate with empirical norms — modestly for self-paced reading and more strongly for eye-tracking data.

2. We demonstrate that, for both memorability and reading times, fine-tuning on a few hundred examples yields predictions that are strongly correlated with empirical norms — exceeding the predictive power of simple, interpretable baselines. This shows that via fine-tuning, the prompting of LLMs for psycholinguistic norms can be extended to sentence-level norms, not just word-level features.

The remainder of the paper is organized as follows. Section 2 discusses the data, models, and procedures used in the evaluation. Section 3 presents the results, which are then discussed in Section 4. We conclude by discussing implications for the intersection of psycholinguistics and NLP, and the limitations and caveats of this approach.

Method	Question Answered	Example
Interpretable Model Features	Does a specific hypothesis hold for the relationship between a model-based and a psycholinguistic feature?	Model surprisal, model embedding distinctiveness, attention weights.
Zero-Shot Prompting	How much introspective capacity does a model have about a feature of interest?	Direct Prompting: *On a scale of 1 to 10, estimate the memorability of the word 'apple'. Answer:*
Fine-Tuned Prompting	How much usable information regarding a feature of interest is contained in model representations (accessed implicitly)?	As above, but fine-tuned on question-answer pairs derived from supervised data.

Table 1: Comparison of model evaluation techniques.

2 Methods

This section describes the data, models, and procedures used to generate and evaluate LLM predictions of memorability and reading times, across zero-shot and fine-tuned settings. A general overview of the procedure is illustrated in Figure 1.

2.1 Data

Here we introduce the datasets which we use in our model evaluations. We focus on two different but important psycholinguistic domains — memorability and reading times — which have not yet been the target of comparison with LLM predictions. In contrast to past work (e.g., Conde et al., 2025a; Trott, 2024), which has considered word-level features such as the Glasgow word norms (Scott et al., 2019) or the Lancaster sensorimotor word norms (Lynott et al., 2020), the domains of sentence memorability and reading times pose a distinct chal-

lenge for estimating psycholinguistic norms via LLM prompting, because they are *sentence-level* features. For instance, the memorability of a sentence is a property of the entire sentence, influenced by its compositional meaning (Clark et al., 2026). Likewise, while reading times are known to depend on certain stable properties of a word, such as its length, frequency, or age of acquisition (Smith and Levy, 2013; Brothers and Kuperberg, 2021; Luke and Christianson, 2018; Demberg and Keller, 2008; Kennedy et al., 2013), they also depend on its contextual surprisal, which varies from sentence to sentence. Any model that successfully predicts reading time variation across different instances of the same wordform will need to take into account the relationship between multiple words in a sentence.

We also include word memorability as a comparison for sentence memorability. For both types of memorability data, norms are collected not by asking human raters for their judgments, but rather by conducting a repeat detection experiment; this makes these norms inherently more scarce and expensive to acquire. Another challenge of memorability data is its dissociation from human subjective judgments, as reported in prior literature. Isola et al. (2014) report that subjective human judgments of the memorability of images actually correlate *negatively* with empirically measured memorability, while Clark et al. (2026) report that subjective memorability judgments for sentences have a weak correlation of 0.24 with empirical sentence memorability. Therefore, for all of the following datasets — word memorability, sentence memorability, and reading times — we have reason to believe that LLM predictions may not align as well with the ground truth compared to results from the prior literature.

2.1.1 Word Memorability

We use the word memorability data of Tuckute et al. (2025)[1], which contains 2109 English words with empirical memorability scores collected via a behavioral experiment with native English speakers. This experimental paradigm builds on a body of work related to measuring the intrinsic memorability of various classes of stimuli, such as images (Isola et al., 2011) and faces (Bainbridge, 2017). A word's memorability is quantified as the average accuracy of responses across participants within a repeat detection (recognition memory) paradigm, yielding values between 0 and 1. In this paradigm, reporting a novel stimulus as familiar and failing to report a repeat stimulus as familiar are the two sources of incorrect responses.

2.1.2 Sentence Memorability

We use the sentence memorability data of Clark et al. (2026)[2], which contains 2500 English sentences with empirical memorability scores collected via a behavioral experiment with native English speakers, following the same experimental paradigm as Tuckute et al. (2025), thereby resulting in scores between 0 and 1. Table 2 shows examples of high- and low-memorability sentences from the dataset.

Sentence	Memorability
Does olive oil work for tanning?	0.98
Scott cried, pursing his pink lips.	0.89
The weather was warm and dry.	0.79
I can't get hold of him.	0.72
We want to make it better.	0.56

Table 2: Example sentences from the dataset of Clark et al. (2026), with human-derived memorability scores. A score of 0.98 means that 98% of human familiarity judgments to a sentence were correct.

2.1.3 Self-Paced Reading Times

We use the reading time data from the Natural Stories Corpus (Futrell et al., 2021)[3], which used self-paced reading (Aaronson and Scarborough, 1976; Mitchell and Green, 1978) to gather average reading durations for words in naturalistic stories. In this paradigm, speakers are presented with one word at a time on a screen, and advance to the next word by pressing a key. Reading duration (in milliseconds) is the time between key presses (while the target word is on screen). The dataset consists of 433 sentences comprising 10,256 words.

2.1.4 Eye-Tracking Reading Times

We use the reading time data from the OneStop Corpus, which used eye-tracking to gather reading times for words in a variety of news articles (Berzak et al., 2025)[4]. In this paradigm, speakers read naturalistically while their eye movements are tracked, yielding reading measures with high

[1] Experiment 1, available at https://github.com/gretatuckute/memorable_words under MIT license.

[2] Available at https://github.com/thomashikaru/sentence_memorability_share under MIT license.

[3] Available at https://github.com/languageMIT/naturalstories under CC BY-NC-SA 4.0 license.

[4] Available at https://osf.io/2prdq/ under CC BY 4.0 license.

spatial and temporal resolution. Multiple reading measures are available, including first fixation duration, gaze duration, and total duration. For our main reading measure in this study, we use gaze duration (the sum, in milliseconds, of the durations of all fixations that land on a word during the first pass, before the gaze leaves the word), as this has an intuitive interpretation as the amount of time used to read a word when it is first encountered. In a different dataset (MECO; Siegelman et al., 2022), gaze duration was shown to be largely predictable based on word length, frequency, and surprisal, with R^2 values of 0.6-0.8 (Opedal et al., 2024). The dataset consists of 1,213 sentences comprising 36,120 words.

2.2 Model Evaluation

Here we describe in detail our procedure for extracting predictions from models in two settings: zero-shot and fine-tuning. The model used for both zero-shot and fine-tuning was `GPT-4o-mini-2024-07-28`. This is in line with the majority of previous work that has relied on models from the GPT-4 family (Conde et al., 2025b).

2.2.1 Zero-Shot

For the zero-shot evaluation, we use OpenAI's batch API to submit all requests. For all requests in both zero-shot and fine-tuned model evaluation, the temperature is set to 0; this forces the model to use greedy sampling, where it always selects the token with the highest probability. This generates nearly deterministic (He and Lab, 2025) outputs, which facilitates reproducibility.

We convert the datasets into a series of JSON requests that are bundled and sent through the API. A processing script inserts each word or sentence of the dataset into the prompt to generate the requests. For example, the prompt used for word memorability is as follows:

```
The memorability of a word measures how persons
remember occurences of words. For example, if
after reading a text they can remember
occurences of that word in the text. You will
give each word a rating from 0 to 1 with three
decimal digits. A rating of 1 indicates that the
 word is memorable and people remember their
occurences in the text. A rating of 0 indicates
that the word is not memorable and people do not
 remember their occurences on a text. Please,
limit your answer to a number with three decimal
 digits. The word is {word}
```

For each entry in the dataset, `{word}` was replaced by the corresponding word of the dataset.

For sentence memorability, a similar prompt was used:

```
You are an expert in psycholinguistics. Your
task is to estimate the memorability of
sentences. You will be presented with a series
of sentences, one at a time. For each sentence,
provide a score between 0 and 1 indicating how
memorable the sentence is, where 0 represents
the lowest memorability and 1 represents the
highest. Only respond with a number between 0
and 1 with two decimal digits.
Memorability is defined as the probability that
a person will remember the sentence after a
certain amount of time. Evaluate the following
sentence: Sentence: {sentence}
```

For both self-paced and eye-tracking reading times, the requested output was a JSON-like structure containing the estimates for each word of the sentence.

```
You are an expert at psycholinguistics. You are
requested to give an estimation on how long does
 it take to read each word of a sentence for an
average reader. Take into accounts factors such
as the difficulty of reading the word and the
context of the word within the sentences. The
estimation must be in milliseconds. As an output
 generate a JSON with tuples of word and
estimation. For example for the sentence I like
cats and the estimations 100ms 200ms 200ms the
output must be {'I':200; 'like': 200; 'cats':
200}. Do include duplicate keys if there are
duplicate words even if the resultant JSON is
not valid. Otherwise generate a valid JSON
object. Do not add any other information. The
sentence is: {sentence}
```

To align the model's output with the input, a Python script was used to align the responses, as the model sometimes added extra words or removed some of them. Because model outputs sometimes contained insertion or deletion errors, a direct one-to-one mapping of the input with the output was not possible. A sliding window algorithm, similar to those used in data networks (Tanenbaum, 1988), was used to align the sentences to handle missing or extra words. The process starts by comparing the first word of the output sentence with the first word of the input sentence. If they match, the algorithm moves to the next pair of words and repeats the comparison until either a mismatch occurs or the end of the sentence is reached. When a mismatch is detected, the algorithm searches for the output word within a three-word window in the input sentence; if found, the alignment continues from there. Otherwise, the output word is labeled as an insertion and skipped.

2.2.2 Fine-Tuning

We performed Supervised Fine-Tuning (SFT) in which we provided the model with both the prompt and the expected output based on the ground truth. For all fine-tuning processes, 25% of the dataset was used for training and 75% for evaluation. For the word and sentence memorability datasets, the expected output was the raw estimate (a single number), whereas for the reading time datasets, the expected output was a JSON-like structure (as described above). During the training process, the model weights are adjusted to adapt the estimate to the expected value. We used the default fine-tuning API settings, with a fixed learning rate of 1.8. The details of the fine-tuning process are presented in Table 3.

The prompts used for fine-tuning were the same ones used for the zero-shot evaluation. Once a fine-tuning job is created, the training process begins until the performance converges. For all evaluations, the final model checkpoint (after 3 epochs of fine-tuning) was used.

Dataset	# Examples	Loss	Epochs	Batch Size
Word mem.	527	0.885	3	1
Sentence mem.	625	0.567		
Self-paced	108	1.227		
Eye-tracking	303	0.934		

Table 3: Fine-tuning parameters used for each dataset. Note that for the reading time datasets, "# Examples" denotes the number of sentences.

After training the model, the fine-tuned version is stored and can be queried later through the batch API. Once the tuning process was completed, we evaluated its performance with the test dataset using the same methodology as in the zero-shot evaluation.

2.3 Correlation Analysis

For each set of model predictions, we evaluate the correlation between human behavioral measures and the model-generated values. We quantify the correlation using the Pearson correlation coefficient and R^2 values.

2.4 Baselines

In order to compare the performance of model predictions for the norms of memorability and reading times, we establish baselines by choosing three interpretable features from the literature, argued to strongly correlate with each psycholinguistic feature of interest. Using 100 random 0.75/0.25 train/test splits of the data, we fit linear regressions using each predictor alone, as well as all three combined, on the training data, and then evaluate the R^2 value on the held-out test data. This procedure yields a distribution over R^2 values.

For word memorability, we use the number of meanings, number of synonyms, and word frequency, using values provided in the dataset of Tuckute et al. (2025). In that study, the values for number of synonyms and number of meanings were collected via a human norming study, and word frequency was computed using the Subtlex corpus (Brysbaert and New, 2009). For sentence memorability, we use Sentence-BERT embedding distinctiveness, average word memorability, and average word frequency, using values provided in the dataset of Clark et al. (2026), since these were identified as predictors of sentence memorability. In that study, Sentence-BERT distinctiveness was computed as the mean cosine distance of a sentence's Sentence-BERT representation to all other sentences in a large and diverse sample of sentences, while average word memorability was estimated using the human norms of Tuckute et al. (2025) and word frequency was taken from the Subtlex corpus and averaged across words in a sentence.

For the reading time norms, we establish baselines using the interpretable features of word length, frequency, and contextual surprisal, following past work (Demberg and Keller, 2008; Brothers and Kuperberg, 2021; Smith and Levy, 2013; Wilcox et al., 2023; Opedal et al., 2024, inter alia). Word length was defined simply as the number of characters in the orthographic representation of the word. Frequency was computed using the `wordfreq` package (Speer, 2022) for Python. Surprisal was computed using the `GPT-2` language model (Radford et al., 2019) and the `wordsprobability` Python package (Pimentel and Meister, 2024).

3 Results

This section presents and briefly discusses the results for each of the datasets[5].

[5]The results are available at: link removed for double blind review.

3.1 Word Memorability

Zero-shot model predictions are uncorrelated with empirical word memorability scores, while a fine-tuned model achieves an R^2 of 0.55 (Figure 2). This exceeds the mean R^2 of 0.28 using the combined baseline predictors of number of meanings, number of synonyms, and frequency (Figure 6).

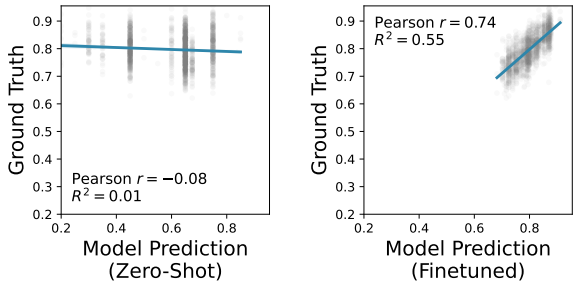

Figure 2: Visualization of the relationship between model predictions and ground truth norms for word memorability, in the zero-shot setting (left) and the fine-tuned setting (right).

3.2 Sentence Memorability

Zero-shot model predictions are uncorrelated with empirical sentence memorability scores, while a fine-tuned model achieves an R^2 of 0.42 (Figure 3). This exceeds the mean R^2 of 0.32 using the combined baseline predictors of Sentence-BERT distinctiveness, average word-level memorability, and average word frequency (Figure 6).

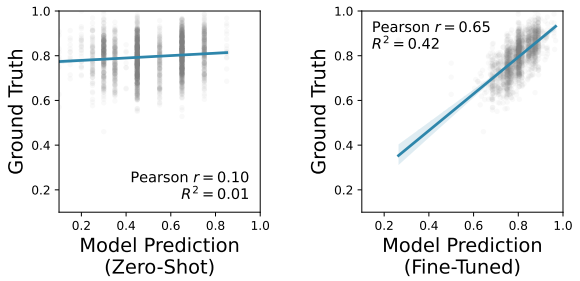

Figure 3: Model predictions vs. ground truth norms for sentence memorability, in zero-shot and fine-tuned settings.

3.3 Reading Times

For the Natural Stories Corpus, zero-shot model predictions are uncorrelated with empirical sentence memorability scores, while a fine-tuned model achieves an R^2 of 0.14 (Figure 4). This is considerably lower than the R^2 values attained by fine-tuned models on the memorability data, but higher than the correlation of 0.08 using the combined baseline predictors (Figure 6).

Interestingly, we observe a qualitatively different pattern for eye-tracking reading times from the OneStop Corpus (Figure 5). The zero-shot model attains an R^2 of 0.37, while the fine-tuned model attains $R^2 = 0.53$. Thus, the fine-tuned model but not the zero-shot model exceeds the correlation of 0.48 using the combined baseline predictors (Figure 6).

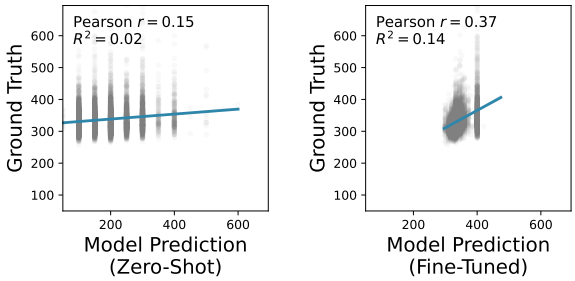

Figure 4: Model predictions vs. ground truth norms for self-paced reading times (Natural Stories Corpus), in zero-shot and fine-tuned settings.

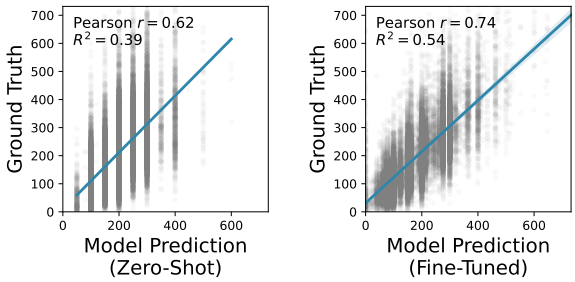

Figure 5: Model predictions vs. ground truth norms for eye-tracking reading times (OneStop Corpus), in zero-shot and fine-tuned settings.

Consistent with known differences between Self-Paced Reading and Eye-Tracking, we find considerable differences in the degree to which the baseline predictors of surprisal, frequency, and length are able to predict reading time measures across the two datasets of Natural Stories and OneStop (Figure 6). We note that our baseline results for OneStop are consistent with the work of Opedal et al. (2024), who found that length and frequency explain a greater deal of variance in reading times, compared to contextual surprisal.

4 Discussion

This section discusses the key insights from the experimental results.

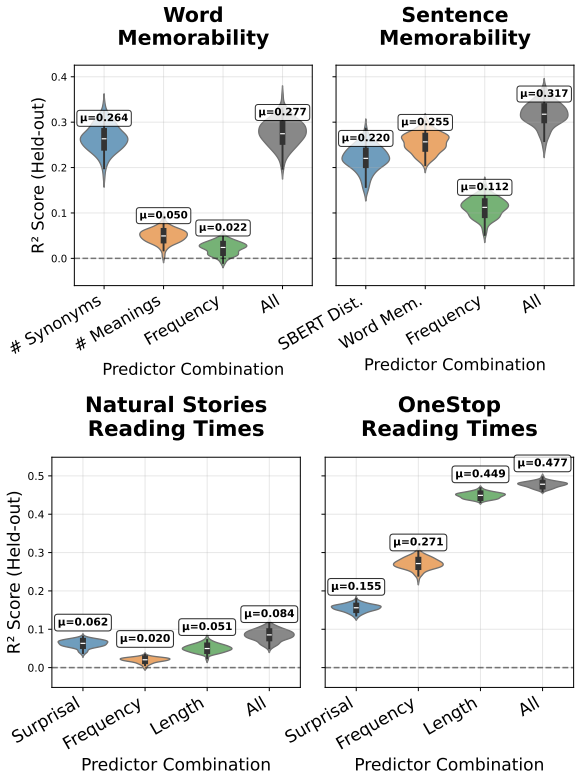

Figure 6: The distribution of R^2 values when predicting a psycholinguistic norm from theoretically motivated baseline predictors, for word memorability, sentence memorability, self-paced reading, and eye-tracking reading times. 'All' denotes a regression with all three baseline predictors.

4.1 LLMs can predict sentence-level norms via fine-tuning

The task of generating reading times for each word in a sentence is considerably more complex than estimating, for example, the valence of a single word. The same applies to estimating the memorability of a sentence. This is because both of these norms involve considering the ways in which multiple words in a sentence interact with each other. For instance, one of the most memorable sentences in the study of Clark et al. (2026) is *Does olive oil work for tanning?*; the memorability of this sentence cannot simply be reduced to the sum of word-level features, but involves the compositional meaning of the words in relation to each other.

Despite this challenge, LLMs are capable of producing estimates that correlate with human behavior when fine-tuned on a small set of supervised data. For both memorability and reading times, fine-tuning achieves a correlation with the ground truth that exceeds that of simple, theoretically motivated baseline predictors (Figure 6). This is consistent with previous results for word-level norms (Conde et al., 2025b), showing that the same general paradigm can be extended to the sentence level. This means that LLMs can potentially be used to predict those norms which are more difficult to collect than word-level norms which rely only on subjective judgments. We also note that the improvement is not attributable simply to high performance on words seen during fine-tuning — for the memorability experiments, the evaluation was conducted on entirely held-out stimuli. For the reading time experiments, all test sentences were held-out, though some individual wordforms were seen in both fine-tuning and testing; model prediction accuracy was high even for words which had not been seen during fine-tuning.

Crucially, in all datasets, the R^2 value attained by the fine-tuned prompting method exceeds that of three combined theoretically motivated baseline predictors. This demonstrates that the prompting method not only can capture the variance explained by these interpretable predictors, but captures additional variance as well; it is possible that several more manually selected predictors of diminishing marginal explanatory power would be required to match the predictive power of the fine-tuned prompted model predictions.

On a theoretical level, this may suggest that the rich distributed representations of words produced by language models encode sufficient information about a diverse range of psycholinguistic behavioral measures, such that fine-tuning on a small dataset enables reliable decoding of these features from the existing model representations (as opposed to learning the relationship from scratch). On a practical level, this method offers a way for psycholinguists to develop predictive models that can estimate psycholinguistic norms for held-out data. While this can introduce challenges in interpretability, the approach may be useful in settings such as the development of experimental materials. One possible use case is ensuring matched control stimuli, as has previously been done with the A-Maze variant (Boyce et al., 2020) of the Maze reading task (Forster et al., 2009).

4.2 Zero-shot performance varies widely across domains

In our results, we observed that for word and sentence memorability, zero-shot model predictions were essentially completely uncorrelated from human behavior. We speculate that the features which

make words and sentence memorable may not be obvious or transparent, consistent with findings from the memorability literature showing that humans themselves are poor judges of memorability in domains such as images (Isola et al., 2014). Meanwhile, the features that correlate strongly with reading times are relatively simple and interpretable in comparison — basic properties of words such as length and frequency, as well as contextual features such as their predictability given preceding sentential context (Hale, 2001; Smith and Levy, 2013; Wilcox et al., 2023, 2020), which may be particularly well-aligned with the next-word prediction training objective of LLMs. Thus we speculate that zero-shot prompting of reading times from LLMs is more effective in extracting predictions that align with human behavior, compared to memorability.

4.3 Differences between self-paced reading and eye-tracking

We also observe considerable differences in the performance of models when comparing self-paced reading and eye-tracking. Eye-tracking remains the gold standard for reading time data, because participants are able to read naturalistically and because the paradigm allows both high spatial and temporal resolution. In self-paced reading, by comparison, there are well-established "spillover" effects (Rayner, 1998; Smith and Levy, 2013) stemming from the rapid pressing of keys and the latency between reading and motor actions. Additionally, the paradigm is somewhat divorced from reading in the wild. Fine-tuning still yields an improvement in predicting self-paced reading times, compared to zero-shot prompting, but the predictive power may be limited by the noise ceiling of the human data.

Figure 7 shows the correlation between model-predicted reading times and the ground truth values as a function of word position within sentence, for the NaturalStories and OneStop corpora. We observe that for the noisier self-paced reading data (Natural Stories), the correlation is highest in earlier parts of the sentence (with the exception of the very beginning of the sentence). Meanwhile, for eye-tracking data (OneStop), the correlation between model predictions and the empirical norms decreases slightly but remains above 0.6 even for word positions much further into the sentence. We note that the fine-tuning data naturally contains fewer examples of late word positions than early word positions. Thus, a single prompt can generate model predictions that correlate with human eye-tracking RTs across a long timescale, but for noisier self-paced reading RTs, model predictions become noisier with word position.

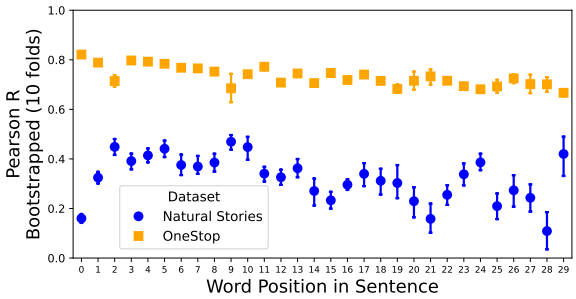

Figure 7: Correlation of fine-tuned model prediction to ground truth for different word positions in a sentence.

5 Conclusion

In conclusion, this work presents several novel findings. First and foremost, this work demonstrates that prompting LLMs for psycholinguistic norms can be extended to sentence-level norms — the memorability of an entire sentence, or the reading time of a word in context — not just word-level features, by using a simple and straightforward supervised fine-tuning strategy. We also showed that the reliability of zero-shot LLM predictions for psycholinguistic norms varies considerably by domain, with the predictions for both word and sentence memorability being uncorrelated with empirical norms. Across domains, fine-tuning on a few hundred examples is sufficient to align the model predictions with empirical values, even beating strong, theoretically motivated baselines reported in the literature.

While the applications of this method in psycholinguistics are promising, our results also suggest that practitioners must be wary of trusting the zero-shot predictions of LLMs on psycholinguistic norming tasks (Hu and Levy, 2023), and careful validation against human data is recommended (Conde et al., 2025b). Future work may target a comprehensive application of this method to other language model families and additional human languages, in order to evaluate the generalizability of these results.

Limitations

In this section, we acknowledge several limitations of our study.

First, due to computational limitations, we performed evaluations on only a single family of LLMs. Future work can consider whether there are meaningful differences in the efficacy of the fine-tuning approach across model architectures, sizes, and families.

Second, the fine-tuning was done with a single, relatively small split of the available human data for training and evaluation. It would be of interest to explore different splits to see if the quality of model predictions improves as more data is used for the fine-tuning.

Another limitation is the present study's exclusive focus on English. It remains an open question whether prompting works as well in lower-resource languages or languages with very different linguistic properties, such as agglutinative languages or those with non-alphabetic writing systems. This limitation also reflects the broader WEIRD bias (Western, Educated, Industrialized, Rich, Democratic) highlighted in cognitive science and NLP, where research has tended to focus on a narrow set of languages and populations that are not representative of global diversity.

Finally, we echo existing calls for caution (Gao et al., 2025; Dentella et al., 2023) regarding the use of LLM outputs as a substitute for, rather than a noisy estimate of, human psycholinguistic norms, especially in zero-shot settings without careful validation against ground-truth values.

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A Appendix: Use of Artifacts and Models

We utilize the `GPT-4o-mini-2024-07-28` language model via the OpenAI API.

We also utilize existing datasets from Tuckute et al. (2025) (MIT License), Clark et al. (2026) (MIT License), Futrell et al. (2021) (CC BY-NC-SA 4.0 license.), and Berzak et al. (2025) (CC BY 4.0), which are publicly available via GitHub or OSF. We use this data purely for research purposes.

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