Fine-Grained Prediction of Reading Comprehension from Eye Movements

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Abstract

Can human reading comprehension be assessed from eye movements in reading? In this work, we address this longstanding question using large-scale eyetracking data over textual materials that are geared towards behavioral analyses of reading comprehension. We focus on a fine-grained and largely unaddressed task of predicting reading comprehension from eye movements at the level of a *single question over a passage*. We tackle this task using three new multimodal language models, as well as a battery of prior models from the literature. We evaluate the models' ability to generalize to new textual items, new participants, and the combination of both, in two different reading regimes, ordinary reading and information seeking. The evaluations suggest that although the task is highly challenging, eye movements contain useful signals for fine-grained prediction of reading comprehension.[1]

1 Introduction

Reading comprehension is an indispensable skill for successful participation in modern society. Consequently, many efforts and resources are invested in the development of reading comprehension assessments by educational institutions and commercial companies. The standard, and to date the only practical way to assess reading comprehension is through behavioral tasks, most commonly reading comprehension questions. However, despite its clear value and ubiquitous use, this approach is extremely time-consuming and costly, which severely limits the volume and public availability of reading comprehension tests. Further, this testing methodology relies on *offline* behavioral signals – the end responses to a few select reading comprehension questions, and has no ability to trace the rich *online* reading comprehension processes as they unfold over time.

An alternative vision for assessing reading comprehension has been emerging in psycholinguistics and the psychology of reading. It posits that reading comprehension may be decoded in real-time directly from eye movements in reading. This vision is rooted in literature that suggests a tight correspondence between eye movements and language comprehension processes (Just and Carpenter, 1980; Rayner, 1998; Rayner et al., 2016, among others). With the rise of modern machine learning and NLP, multiple studies over the past decade attempted to use eye movement data to predict reading comprehension (Copeland et al., 2014; Ahn et al., 2020; Reich et al., 2022; Mézière et al., 2023b, among others). This line of work suggests that although in some cases various aspects of reading comprehension can be predicted from eye movements with above-chance performance, this problem is extremely challenging. Thus, despite the advances so far, predictive modeling of reading comprehension from gaze is still in its infancy.

A number of factors have been hindering progress in this area. One is the paucity and small size of reading comprehension data paired with eye movements. Second, the task of reading comprehension prediction has thus far been predominantly formulated as prediction of *aggregated scores across multiple questions* rather than prediction of comprehension at the resolution of an individual question. Further, reading comprehension has been primarily studied when the reader has no specific goals with respect to the text beyond general comprehension, a regime that we refer to as *ordinary reading*. Many other reading regimes common in daily life, such as explicit information seeking, remain largely unaddressed. Finally, despite the dramatic progress in machine learning and NLP in recent years, effective joint modeling of text and eye movements remains a nascent and challenging domain of investigation.

In this work, we take a step forward in advancing

[1] Our code and data are available at https://github.com/lacclab/Cognitive-State-Decoding.

the state-of-the-art in eye movement-based prediction of reading comprehension by combining new models, new data, and systematic evaluations. Our primary contributions are the following:

- **Task**: we address the challenging and largely unaddressed task of predicting comprehension at the level of a *single reading comprehension question over one passage*. Addressing this task is enabled by OneStop Eye Movements, an extended version of the dataset collected by Malmaud et al. (2020), the largest eyetracking for reading comprehension dataset to date with 486 multiple-choice questions and 19,440 question responses from 360 participants.

- **Modeling**: We develop three new models combining text and eye movements based on the transformer encoder architecture: RoBERTa-QEye, MAG-QEye, and PostFusion-QEye. These models address both test format-agnostic and multiple-choice specific variants of the task.

- **Reading Regimes**: we study not only ordinary reading but also information seeking, a highly common but understudied reading scenario for human reading comprehension.

- **Evaluation**: We evaluate our models against a battery of existing models for prediction of reading comprehension from eye movements, and a strong text-only baseline. To this end, we use a detailed evaluation protocol targeting three different levels of model generalization: new participant, new textual item, and the combination of both.

2 Related Work

Our study contributes to an existing body of work on prediction of reading comprehension from eye movements in reading. To address various aspects of this task, prior studies used a wide range of models, including linear models (Mézière et al., 2023b,a), kernel methods (Makowski et al., 2019), feed-forward networks (e.g. Copeland et al., 2014), CNNs (Ahn et al., 2020) and RNNs (e.g. Ahn et al., 2020; Reich et al., 2022). These were typically applied to prediction of aggregated comprehension scores over multiple items. In this work, we evaluate multiple models from prior work on the single-item reading comprehension task.

While transformer models (Vaswani et al., 2017), have been used for joint modeling of eye movements and text (e.g. Deng et al., 2023; Yang and Hollenstein, 2023), they have not been applied to the problem of reading comprehension prediction from eye movements. In this work we introduce three new transformer models which draw on multimodal transformers, in particular MAG (Rahman et al., 2020) which integrated text, speech and vision for sentiment analysis, and language vision models such as VisualBERT (Li et al., 2019) (see Zhu et al. (2023); Xu et al. (2023) for reviews).

Most prior studies on reading comprehension prediction from eye movements relied solely on eye movement features (Copeland et al., 2014; Southwell et al., 2020; Ahn et al., 2020; Mézière et al., 2023b,a), while a few combined eye movements with properties of the underlying text (Martínez-Gómez and Aizawa, 2014; Makowski et al., 2019; Reich et al., 2022). In the current work, we take the latter, under-explored approach. The importance of combining eye movements with attributes of the text is motivated by a large literature in the psychology of reading which points to systematic effects of linguistic properties of the text on reading times (Rayner, 1998; Rayner et al., 2004; Kliegl et al., 2004; Demberg and Keller, 2008; Smith and Levy, 2013, among others), in particular in the context of reading comprehension (Just and Carpenter, 1980) and linguistic proficiency (Berzak et al., 2018; Berzak and Levy, 2023).

While highly informative, existing work is critically limited by small data, especially with respect to the number of available questions and participants. For example, Copeland et al. (2014) have 9 text pages, 18 questions and 39 participants. SB-SAT (Ahn et al., 2020), the only publicly available eyetracking dataset for reading comprehension, has 22 text pages, 20 questions, and 95 participants. The small size of previously used datasets severely limits the potential of NLP and machine learning models for reading comprehension prediction. At the same time, the reading comprehension component of broad coverage eyetracking datasets such as MECO (Siegelman et al., 2022) and CELER (Berzak et al., 2022) comprises only simple comprehension questions that serve as attention checks, and as such are not well suited for studying reading comprehension. OneStop, used here, has a large number of items, participants and questions, enabling to meaningfully address item-level prediction of comprehension.

Prior work varies in experimental designs. In several studies, multiple questions are presented after reading a multi-screen text without the ability to return to the text (Makowski et al., 2019; Ahn et al., 2020; Reich et al., 2022). This is advantageous in the separation of text reading and question answering, but can lead to loose relations between eye movements and question-answering behavior due to memory limitations. In other studies, such as Copeland et al. (2014), participants can switch back and forth between the text and the questions. This creates a complex mix of ordinary reading and information seeking components which are difficult to disentangle. In OneStop, a single question appears immediately after reading a single text page, setting a middle ground between the two primary existing approaches for question presentation, and alleviating their main disadvantages. At the same time, it includes a question preview manipulation which allows to systematically compare reading comprehension in ordinary reading and question guided information seeking.

An additional limitation of prior work is the scope and nature of the evaluations. With the exception of Copeland et al. (2014), both training and evaluation were previously carried out over *aggregated responses* across multiple questions, and in some cases also across multiple texts. These approaches, which focus on measuring overall comprehension, do not enable testing direct links between eye movements and understanding specific aspects of the text. In several studies (Martínez-Gómez and Aizawa, 2014; Makowski et al., 2019; Ahn et al., 2020; Reich et al., 2022), an additional step was taken, binning comprehension scores into two binary categories, high versus low comprehension, thus further simplifying the task.

A second important evaluation limitation in prior work is evaluations in which eyetracking data for the test participants and items is used in the training set. In particular, except for Makowski et al. (2019), to our knowledge no work has evaluated reading comprehension prediction when neither the participant nor the item appears in the training data. This evaluation regime is needed to fully characterize model generalization ability. Importantly, even in less challenging regimes and with aggregated scores and binning, model performance in prior work is typically only modestly higher than chance level. More stringent evaluations without binning comprehension scores (Martínez-Gómez and Aizawa, 2014), or with held-out participants and/or items (Makowski et al., 2019; Reich et al., 2022) tend to exhibit chance level performance. These results suggest that generalization in reading comprehension prediction is highly challenging.

3 Eyetracking Data

We use OneStop Eye Movements, an extended version of the dataset collected by Malmaud et al. (2020). OneStop is a corpus of eyetracking for reading over the textual materials of OneStopQA (Berzak et al., 2020). The data was collected using an Eyelink 1000+ eyetracker at a sampling rate of 1000Hz. In this dataset, 360 adult native English participants read newswire articles from the Guardian, and answer a multiple-choice reading comprehension question about each paragraph. The dataset includes 30 articles divided into 162 paragraphs. The average paragraph length is 109 words. Each paragraph has 3 possible questions, corresponding to a total of 486 questions.

The articles are divided into three 10-article batches, where each participant is assigned to one batch. In each trial of the experiment, participants read a paragraph and then proceed to answer one of the three possible questions on a new screen, without the ability to return to the paragraph. 180 participants are in an ordinary reading (Gathering) regime where they do not see the question prior to reading the paragraph. The remaining 180 participants are in an information seeking regime (Hunting) where they are presented with the question (but not the answers) prior to reading the paragraph. The total number of trials is 19,440, split equally across the two reading regimes. This corresponds to 40 responses per question, 20 for each regime–paragraph combination. The total number of word tokens over which eyetracking data was collected in OneStop is 3,827,216.

The underlying textual materials and reading comprehension questions follow the STARC annotation framework (Berzak et al., 2020), where answer A is the correct answer, answer B is a miscomprehension of the information required to answer correctly, C refers to another part of the text that is unrelated to the question and D has no textual support. These answer types correspond to an ordering of the answers by degree of comprehension. Table 1 presents a summary of the framework along with answer choice statistics in the OneStop eyetracking data.

Answer	Category	Degree of Comprehension	Gathering	Hunting
A	Correct	Full comprehension	7,890 (81.2)	8,450 (86.9)
B	Incorrect	Identified question-relevant information	1000 (10.3)	744 (7.7)
C	Incorrect	Some degree of attention to the text	568 (5.8)	374 (3.8)
D	Incorrect	No evidence for comprehension	260 (2.7)	152 (1.6)

Table 1: Summary of the STARC annotation framework for answer types A–D, their corresponding degree of comprehension, and number of trials in which each answer type was chosen in OneStop. Values in parentheses are percentages by reading regime.

4 Tasks

4.1 Correct versus Incorrect Comprehension

The primary task we address is item-level prediction of whether a participant will respond correctly to a single question about a paragraph from the participant's eye movements over the paragraph. For each paragraph p and a corresponding question q^p, the possible answers are $Ans^{q^p} = \{a_1^{q^p}, a_2^{q^p}, a_3^{q^p}, a_4^{q^p}\}$. Note that the correct answer A and the three distractors $\{B, C, D\}$, as specified in Section 3, are randomly mapped per trial to a_1 through a_4. The set of p, q^p, and optionally Ans^{q^p}, depending on the setup, defines a *textual item* W. Given a participant S tested on item W, where the participant's eye movements over the paragraph are $Eyes_S^p$, the complete trial information is $Trial_S^W := \{W, Eyes_p^S\}$.

The prediction problem can then be formulated as a binary classification task, where we predict whether the participant will answer the question correctly. Formally, we predict a binary score,

$$Score : Trial_S^W \rightarrow \{0, 1\} \qquad (1)$$

where 1 indicates a correct answer (A) and 0 indicates an incorrect answer $(B/C/D)$.

Note that this task formulation abstracts away from the multiple-choice format in that the specific answers are an optional input. This allows assessing comprehension without depending on the format of the subsequent assessment task (e.g. answer choice, answer production), nor its details such as the number of answer choices and their specific content in the multiple-choice format. We further note that the paragraph text is also optional. The combination of these task characteristics enables applying prior models from the literature, all of which predict a binary outcome without taking into account the answers, and some of which use only eye movements without the text.

4.2 Specific Answer Choice

We further address a task that takes advantage of the multiple-choice assessment format. In this task, given the answers, we predict which *specific answer* the participant will select,

$$Score : Trial_S^W \rightarrow \{a_1, a_2, a_3, a_4\} \qquad (2)$$

5 Models

We develop three models, RoBERTa-QEye, MAG-QEye and PostFusion-QEye, all of which combine text and eye movements information, and rely on the transformer language model encoder. Specifically, we use the RoBERTa$_{\text{LARGE}}$ model (Liu et al., 2019). Each of these models introduces a different strategy for combining text with eye movements. RoBERTa-QEye augments the textual input with additional eye movement features. MAG-QEye uses eye movement information to modify contextualized word representations. PostFusion-QEye processes text and eye movements separately and combines them via cross-attention mechanisms. We further adjust a number of prior models from the literature for the single-item reading comprehension prediction task.

Eye Movement Feature Representations The eyetracking record is commonly represented as a scanpath consisting of fixations (periods in which the gaze position is stable) and saccades (rapid transitions between fixations). The examined models represent this information in three different ways, in increasing level of granularity.

- **Global**: Summarizing fixation and saccade information across all the words in the input.
- **Words**: Summarizing fixation and saccade information for each word.
- **Fixations**: Accounting for each fixation and its preceding and following saccade.

Our new models focus on the word and fixation level approaches, using a variety of eye movement measures from the psycholinguistic literature. As reading times are known to be affected by linguistic word properties such as predictability, frequency, and length (Rayner et al., 2004; Kliegl et al., 2004; Rayner et al., 2011), which are not directly encoded in word embeddings, we further add such properties to the eye movement representations to allow the models to learn eye movements-word property interactions. The strength of such interactions has been shown to be indicative of the readers' linguistic proficiency (Berzak et al., 2018; Berzak and Levy, 2023), which is directly related to reading comprehension. The eye movement and linguistic word property features used in all the models are listed in Appendix A. Note that two different feature sets are used for representing eye movements at the word and fixation levels. Figure 1 presents an example of an eye movement trajectory over a paragraph and a schematic visualization of the word-level feature extraction approach.

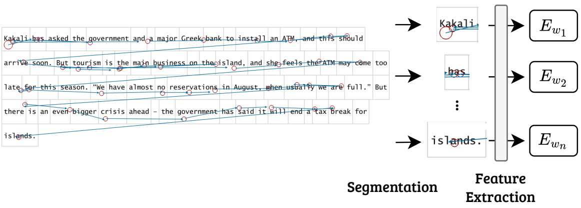

Kakali has asked the government and a major Greek bank to install an ATM, and this should
arrive soon. But tourism is the main business on the island, and she feels the ATM may come too
late for this season. "We have almost no reservations in August, when usually we are full." But
there is an even bigger crisis ahead – the government has said it will end a tax break for
islands.
Kakali
has
⋮
islands.
E_{w_1}
E_{w_2}
E_{w_n}
Segmentation
Feature Extraction

Figure 1: Example of an eye-movement scanpath over a paragraph and a schematic representation of word-level feature extraction, resulting in a vector E_{w_i}, an eye movements and linguistic word properties feature representation for each word.

5.1 RoBERTa-QEye

RoBERTa-QEye incorporates eye movements as additional input sequences to RoBERTa by projecting them to the word embedding space. An overview of the architecture is depicted in Figure 2a. The model is implemented in two variants, one with word-level features and one with fixation-level features. Both variants combine a textual input Z_W with eye movements input Z_{E_P}.

The textual representation Z_W is the word embedding sequence $[\texttt{CLS}; p; \texttt{SEP}; q^p; [Ans^{q^p}]; \texttt{SEP}]$, where p is the paragraph, q^p is the question, $[Ans^{q^p}]$ are optional answers, and SEP is a separator token. The eye movement representation for the paragraph $Z_{E_P} = [Z_{E_{w_1}}, ..., Z_{E_{w_n}}]$ consists of a representation for each fixation or word i as $Z_{E_{w_i}} = \text{FC}(E_{w_i}) + \text{Emb}_{\text{pos}}(i) + \text{Emb}_{\text{eye}}$, where E_{w_i} are the eye movement and word property features and FC is a fully connected layer projecting this feature representation to the word embedding space. $\text{Emb}_{\text{pos}}(i)$ is the positional embedding of the i-th word or fixation, initialized to the model's original positional embedding, which ties the eye movement representation to its respective word index. Emb_{eye} is an additional learnable embedding marking the presence of eye movement information. Z_{E_P} is concatenated with the word embedding representation Z_W, separated by a special token $\texttt{SEP}_E$, initialized as SEP. The combined sequence $[Z_{E_P}; \texttt{SEP}_E; Z_W]$ is passed through the transformer encoder language model. The resulting CLS token is then fed to a multilayer perceptron for response prediction.

5.2 MAG-QEye

MAG-QEye, depicted in Figure 2b, modifies the transformer encoder's hidden word representations based on eye movement information. It is an adaptation of the MAG architecture (Rahman et al., 2020), originally developed for multimodal sentiment analysis, to eye movements data. Intuitively, the goal is to emphasize or de-emphasize words based on their respective reading times. Formally, for a given model layer k, each hidden token representation in the paragraph $Z^k_{W_i}$ is shifted by H_{W_i},

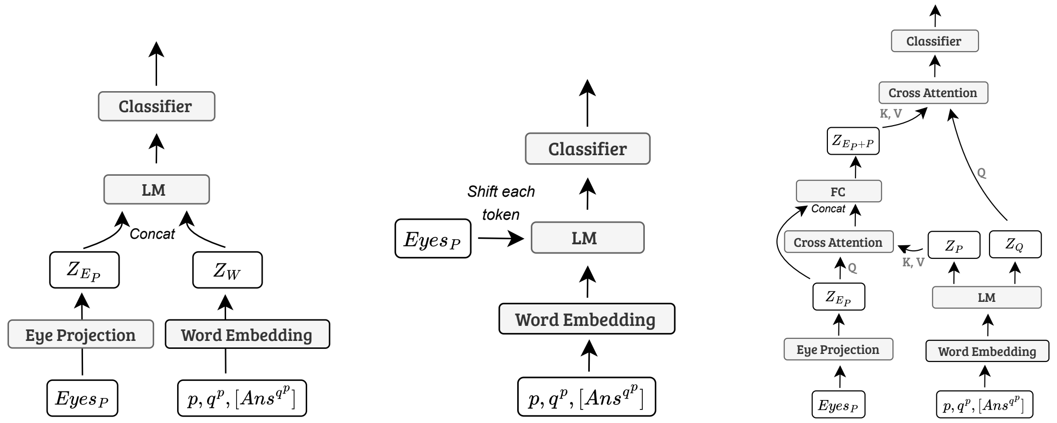
$$\bar{Z}^k{}_{W_i} = Z^k_{W_i} + \alpha H_{W_i} \tag{3}$$

where H_{W_i} is a scaled version of eye movements E_{W_i} transformed into the word embedding space. The final resulting CLS token is passed through a multilayer perceptron classifier. Appendix E.1 provides a detailed description of the architecture.

5.3 PostFusion-QEye

PostFusion-QEye, depicted in Figure 2c, processes text and eye movements separately and combines their representations through two cross-attention mechanisms. The primary objective of these mechanisms is to transform both text and eye movement data into a unified space, which we refer to as the *reading space* while taking into account the reading comprehension prediction task.

The input paragraph is passed through a language model to obtain contextualized embeddings Z_P. The eye movement input features are processed through two 1D convolution layers, resulting in the eye movement representation Z_{E_P}. Cross-attention is then applied between the paragraph embedding Z_P and Z_{E_P}, with eye movements as the query and text embeddings as the key and the value. This step modifies the paragraph words based on the eye movements. The output is provided along with Z_{E_P} to a fully connected layer, yielding Z_{E_P+P}, a projection of the two into a shared space. Another cross-attention layer is applied between Z_{E_P+P} (as key and value) and the question embedding Z_Q (as query), weighting the shared representation by the relevance to the



(a) RoBERTa-QEye (b) MAG-QEye (c) PostFusion-QEye

Figure 2: Model architectures. RoBERTa-QEye (a) treats eye movements as additional input features. MAG-QEye (b) uses eye movement information to modify contextualized word representations. PostFusion-QEye (c) processes text and eye movements separately and combines them via cross-attention mechanisms. Model input: $Eyes^P$ represents the participant's eye movements over the paragraph p, q^p is a corresponding question and $[Ans^{q^p}]$ are optional answer choices.

question. The output of this step is passed to a multilayer perceptron classifier to predict the response.

5.4 Multiple-Choice Task Adaptation

For the specific-answer prediction task, we add to the model input the answer choices: $[a_1^{q^p}, a_2^{q^p}, a_3^{q^p}, a_4^{q^p}]$. The answer choices are given to the model in a randomized order, as presented to the participants.

5.5 Baseline Models

We compare the proposed models to a number of eye movement models from prior work. We focus on models that were either designed for reading comprehension prediction or can be adjusted to the binary task with minimal modifications. As none of the prior models allow encoding of answers, we cannot apply them to the multiple-choice task.

Logistic Regression (Mézière et al., 2023b) Based on Mézière et al. (2023b) who used linear regression for reading comprehension prediction. We use the same feature-set which includes reading speed, and global averages of standard eye movement measures.

CNN (Ahn et al., 2020) Similarly to Mézière et al. (2023b), this model is based only on eye movement information, without the underlying text. It uses the fixation sequence, represented by x and y coordinates on the screen, fixation durations, and pupil size, which are passed through a Convolutional Neural Network (CNN) to predict a binary comprehension outcome.

BEyeLSTM (Reich et al., 2022) A model for predicting reading comprehension from eye movements which represents both the fixation sequence and text features, combining LSTMs with affine transformations. BEyeLSTM outperforms the CNN model of Ahn et al. (2020), on the high versus low comprehension task with SB-SAT.

Eyettention (Deng et al., 2023) This model was originally developed for scanpath prediction. Eyettention is a word sequence encoder and a fixation sequence encoder that uses a pre-trained BERT (Devlin et al., 2019) and an LSTM (Hochreiter and Schmidhuber, 1997), with a cross-attention mechanism for the alignment of the input sequences. We adjust this model for prediction of reading comprehension by using global cross-attention instead of windowed attention, and represent the scanpath using the last hidden representation. Further details on this model are provided in Appendix E.

5.6 No Eye Movements Baselines

We further introduce two baselines with no eye movements. The first is a majority class baseline. The second is **text-only RoBERTa**. This baseline is of special importance as it is able to take into account item difficulty as reflected in the item textual characteristics and the distribution of item responses in the training data. To our knowledge, no previous reading comprehension prediction method was benchmarked against this kind of baseline.

6 Experimental Setup

6.1 Evaluation Protocols

We evaluate the models in three evaluation regimes that test different aspects of model generalization.

- **New Participant**: No eyetracking data is available for the given participant, but eyetracking data from other participants is available for the given item (paragraph).
- **New Item**: No eyetracking data is available for the item, but prior eyetracking data is available for the participant on other items.
- **New Participant and Item**: No prior eyetracking data is available for the participant nor for the item.

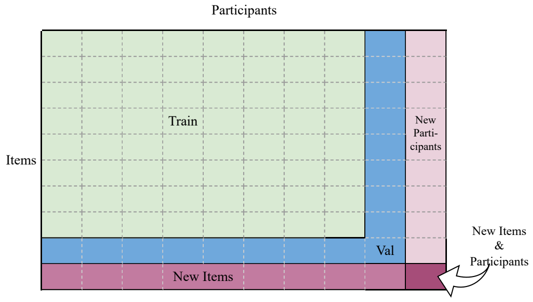


Figure 3: A schematic depiction of one data split, divided into train, validation, and the three test regimes.

We perform model training, selection, and evaluation separately for the ordinary reading and information seeking parts of the data, with 10-fold cross-validation for each part. Figure 3 presents schematically one of the 10 data splits. In each split, approximately 64% of the data is allocated for training, 17% for validation, and 19% for testing. The test data is further divided into 9% in the New Participant, 9% New Item, and 1% New Participant and New Item regimes.[2]

Because the data is unbalanced across classes, we use balanced accuracy as the evaluation metric. As prior work has shown considerable differences in reading behavior between the ordinary reading and information seeking reading conditions (Hahn and Keller, 2023; Malmaud et al., 2020; Shubi and Berzak, 2023), we train and evaluate the models on each type of trials separately. We perform hyperparameter optimization and model selection for each split, and report balanced accuracy results on the aggregation of the predictions across the 10 test sets. We assume that at test time the evaluation regime of the trial is *unknown*. Model selection is therefore based on the entire validation set of the split. As prior models from the literature were developed for different tasks and on different datasets, we run a hyperparameter search for each model over a search space that includes the original parameter settings. Hyperparameters are also optimized for the text-only RoBERTa baseline. The number of model parameters, search space, and the full hyperparameter configurations for all the models are provided in Appendix C.

6.2 Training Procedure

We use the AdamW optimizer (Loshchilov and Hutter, 2018) with a batch size of 16, a linear warmup ratio of 0.1, and a weight decay of 0.1, following best practice recommendations from Liu et al. (2019) and Mosbach et al. (2021). We train for a maximum of 10 epochs. To address the unbalanced nature of the data, as shown in Table 1, we sample the same number of trials from each answer class during training. We apply standardization for each feature in E_P, where the statistics are computed on the train set and applied to the validation and test sets, separately for each split.

6.3 Hardware and Software

All neural network-based models were trained using the PyTorch Lighting (Falcon and The PyTorch Lightning team, 2019) library on NVIDIA A100-40GB and A40-48GB GPUs. Further details regarding the hardware, software packages and training procedures are provided in Appendix D.

7 Results

7.1 Correct vs Incorrect Comprehension

In Table 2, we present trial-level reading comprehension prediction results for ordinary reading and information seeking. The best results are achieved by different models under the different evaluation regimes. MAG-QEye achieves the highest balanced accuracy in ordinary reading with a score of 59.2, while PostFusion-QEye performs best in information seeking, with a score of 58.0. In all

[2] In total across the 10 splits, approximately 90% of the trials in the dataset appear in each of the New Participant and New Item evaluation regimes, and 10% in the New Participant and Item regime. Items are assigned to the train, validation and test portions of each split at the *article level*, such that no article is split across different data portions, ensuring generalization to items whose content is unrelated to items seen in training. See Appendix F for further information on the splits.

Binary Reading Comprehension			Ordinary Reading (Gathering)				Information Seeking (Hunting)			
Model	Gaze Representation	Text Representation	New Item	New Participant	New Item & Participant	All	New Item	New Participant	New Item & Participant	All
Majority	None	None	50.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0
Text-only RoBERTa	None	Emb	54.8	63.1	55.2	58.7	51.8	63.1	50.5	57.1
Log. Reg. (Mézière et al., 2023b)	Global	None	53.3	50.8	53.8	52.2	53.2	52.2	52.3	52.7
CNN (Ahn et al., 2020)	Fixations	None	51.0	51.0	51.9	51.1	51.4	51.3	49.2	51.2
BEyeLSTM (Reich et al., 2022)	Fixations	Ling. Feat.	50.6	55.7	51.1	53.0	50.5	55.1	**55.1**	53.0
Eyettention (Deng et al., 2023)	Fixations	Emb + Word Len.	54.8	60.4	**57.1**	57.6	50.5	56.4	52.3	53.4
RoBERTa-QEye	Words	Emb + Ling. Feat.	**55.5**	63.5	52.1	59.1	50.5	**63.8**	51.0	56.8
RoBERTa-QEye	Fixations	Emb + Ling. Feat.	53.3	61.3	**57.1**	57.3	50.3	60.3	50.8	55.1
MAG-QEye	Words	Emb + Ling. Feat.	54.8	**64.1***	53.8	**59.2**	52.5	62.3	51.3	57.1
PostFusion-QEye	Fixations	Emb + Ling. Feat.	54.8	63.5	55.0	58.9	**53.8***	62.7	53.8	**58.0**

Table 2: Results on balanced accuracy for the main binary reading comprehension prediction task (correct vs incorrect comprehension). 'All' denotes results for the aggregation of all the trials across the three test regimes. 'Emb' stands for word embeddings, 'Ling. Feat.' for linguistic word properties. Statistically significant improvements over the text-only RoBERTa baseline, using a paired bootstrap test (Dror et al., 2018), are marked with '*' at $p < 0.05$.

Multiple-Choice Reading Comprehension			Ordinary Reading (Gathering)				Information Seeking (Hunting)			
Model	Gaze Representation	Text Representation	New Item	New Participant	New Item & Participant	All	New Item	New Participant	New Item & Participant	All
Majority	None	None	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0
Text-only RoBERTa	None	Emb	25.3	**33.0**	25.2	29.0	25.0	**31.7**	24.8	28.2
MAG-QEye	Words	Emb + Ling. Feat.	27.9***	32.5	30.4***	30.2**	26.8	30.0	**29.0**	**28.4**
PostFusion-QEye	Fixations	Emb + Ling. Feat.	**29.4****	31.7	**32.9***	**30.6***	**27.5***	27.9	26.7	27.6

Table 3: Results on balanced accuracy for the multiple-choice specific answer prediction task, with MAG-QEye and PostFusion-QEye, the best performing models on the main task (see Table 2). Statistically significant improvements over the text-only RoBERTa baseline, using a paired bootstrap test, are marked with '*' at $p < 0.05$, '**' at $p < 0.01$ and '***' at $p < 0.001$. Note that in some cases higher balanced accuracy scores correspond to lower p-values due to higher variability in the predictions of the minority classes.

the evaluation regimes, the best performing model outperforms the text-only RoBERTa baseline, and in all but one regime (New Item & New Participant) outperforms all the methods from prior work. Text-only RoBERTa turns out to be a key benchmark, whereby most models are below this baseline especially in the New Participant regime.

We note several key trends in the results. First, results in the New Participant regime tend to be higher than in the New Item regime, highlighting the importance and the challenge of generalization to new items. The strong performance of the RoBERTa text-only baseline in the New Participant regime suggests that much of the gains in this regime do not stem from eye movement information, but rather from item properties and statistics. It further underscores the importance of explicit representation of the text; LR, CNN and BEyeLSTM models, which do not include such a representation, perform poorly in the New Participant regime. Finally, for any given model, the ordinary reading regime tends to yield higher accuracies compared information seeking. We hypothesize that this difference could be related to higher variability in reading strategies in information seeking across participants (Shubi and Berzak, 2023).

7.2 Multiple-Choice Task: Predicting Specific Answers

In Table 3 we use the best performing models on the main task, MAG-QEye and PostFusion-QEye, to predict participants' specific answer response among the four provided answers. As mentioned above, prior models from the literature are not applicable for this task. We find that MAG-QEye and PostFusion-QEye outperform the text-only RoBERTa baseline in the two regimes that involve new items, but not in the New Participant regime. The general trends regarding higher performance on the New Participant regime compared to the New Item regime, as well as the stronger within-model performance in ordinary reading compared to information seeking, extend to this evaluation.

7.3 Ablation Study

In Tables 6 and 7 in Appendix B we present two types of ablations that examine the technical properties of the LM backbone used in MAG and PostFusion, and the interaction between eye-movement and linguistic word properties, respectively In the first ablation, we examine the effect of LM backbone properties – size (in number of parameters), pre-training on a QA dataset and weight freezing during training on the results of both MAG and PostFusion. We chose these two models because they show the best overall performance and consistent improvement over the text-only baseline. We find that keeping the LM weights frozen during training consistently degrades performance for both MAG and PostFusion. Additionally, replacing RoBERTa Large with RoBERTa Base led to a decline in overall results. However, using RoBERTa Large pre-trained on the RACE QA dataset (Liu et al., 2019) resulted in improvements within the Gathering reading regime across all evaluation regimes except for the New Item & Participant regime, while no improvements were observed for the Hunting regime.

In the second ablation, we investigate the interaction between eye movements and linguistic word properties by evaluating the impact of removing each feature set from the word-level eye movement representation. MAG was chosen for this analysis as it, along with RoBERTa-QEye Words, allows the removal of eye-movement-related features without retaining the fixation order in the input. This is important as even with removal of eye-movement features themselves, the fixation order still provides implicit information about the gaze trajectory. MAG outperformed RoBERTa-QEye Words in general, making it the preferred model for this ablation. Interestingly, in most evaluation regimes for both Hunting and Gathering, removing linguistic word properties from the full word-level representation improved performance, albeit not significantly.

8 Summary

This paper presents a systematic evaluation of the ability to predict reading comprehension from eye movements in reading at the level of a single question over a single paragraph. We address this task using a range of existing and new models applied to large scale data across several task variants and evaluation regimes. Our experiments indicate that the task at hand is highly challenging, and further highlight the importance of text-only baselines for assessing the added value of eye movements information. However, we do find that moderate improvements over a strong text-only baseline are achievable with the proposed and some of the past modeling approaches.

Given the presented results, the extent to which specific aspects of reading comprehension can be reliably decoded from eye movements signal remains an open question. Additional work on eye movement data analysis, new model architectures, feature representations, and training regimes is needed for making further progress on this question. We envision that the models, tasks, evaluation protocols, and data presented here will serve as a stepping stone for such work, as well as broader scientific investigation of the relations between eye movements and reading comprehension.

9 Ethical Considerations

The eyetracking data used in this work was collected by Malmaud et al. (2020) under an institutional IRB protocol. All the participants provided written consent prior to participating in the eyetracking study. The data is anonymized. Analyses of the relations between eye movements and reading comprehension, and predictive models of comprehension and cognitive state are the primary use cases for which the data was developed.

Automatic reading comprehension assessments from eye movements can potentially address shortcomings of standard assessment methodologies by reducing test development and test taking costs, and enhancing test availability. However, they also introduce potential risks for biased and inaccurate assessments that may put various populations and individuals at a disadvantage. These include non-native speakers, older participants, participants with cognitive impairments, disabilities, eye conditions and others. Much higher model performance than the current state-of-the-art and a thorough examination of potential biases due to factors unrelated to reading comprehension are needed before considering deploying such assessments.

It has previously been shown that eye movements can be used for user identification (e.g. Bednarik et al., 2005; Jäger et al., 2020). We do not perform user identification in this study. We further emphasize that future reading comprehension assessment systems are to be used only with explicit consent from potential users to have their eye movements collected and analyzed.

10 Limitations

Our work has a number of limitations which are related to the experimental design of OneStop. First, the textual data of OneStopQA consists of articles with 4-7 paragraphs. Each question is over the content of a single paragraph. Longer and shorter texts, as well as questions that require integration of information from several paragraphs, are not included. The experimental design does not allow participants to go back and forth between the question and passage, which is a common reading behavior for question answering tasks. Further, participant expectations for upcoming reading comprehension questions, as well as the setting of an in-lab experiment may result in reading patterns that deviate from reading in everyday settings (Huettig and Ferreira, 2022) and could impact the predictive performance of the model.

While our work examines the feasibility of automated assessment of reading comprehension from eye movements, the accuracy of the models presented is still very far from being relevant for deployment in real world scenarios. Our results are further limited to the equipment at hand. Our approach has only been tested using a state-of-the-art eyetracker (Eyelink 1000 Plus) at a sampling rate of 1000Hz. This allows extracting gaze position and duration at a very high temporal resolution and character-level precision. While studies such as Ishimaru et al. (2017) and Chen et al. (2023) have demonstrated predictive modeling capabilities using lower spatial and temporal resolution eye tracking systems, additional work is required to test the feasibility of reading comprehension prediction using such equipment.

Although we use the largest eyetracking for reading comprehension dataset to date, the dataset by Malmaud et al. (2020) is collected from adult native English speakers, with no cognitive impairments, and in the large majority of cases no eye conditions. We acknowledge that this pool of participants excludes multiple populations, including children, elderly, participants with cognitive and physical impairments and others. Future data collection and analysis work is required to test the generalization capabilities and potential biases of the models in other populations.

In this work we assume the availability both of eyetracking data and a pretrained language model for the language at hand. Although lower-resource language-specific models (e.g. Chriqui and Yahav, 2022; Vamvas et al., 2023) or multilingual models (Lai et al., 2023) have been made available, we acknowledge that many languages still lack such models. Similarly, to the best of our knowledge no relevant eyetracking data is currently available for languages other than English. This limits the generality of the results and the potential for developing automated reading comprehension assessments in languages other than English. Additional data collection and language model development work is required to include additional languages.

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A Features

Feature Name	Description
Word-Level Eye Movement Features	
IA_DWELL_TIME	The sum of the duration across all fixations that fell in the current interest area
IA_DWELL_TIME_%	Percentage of trial time spent on the current interest area (IA_DWELL_TIME / TRIAL_DWELL_TIME).
IA_FIXATION_%	Percentage of all fixations in a trial falling in the current interest area.
IA_FIXATION_COUNT	Total number of fixations falling in the interest area.
IA_REGRESSION_IN_COUNT	Number of times interest area was entered from a higher IA_ID (from the right in English).
IA_REGRESSION_OUT_FULL_COUNT	Number of times interest area was exited to a lower IA_ID (to the left in English).
IA_RUN_COUNT	Number of times the Interest Area was entered and left (runs).
IA_FIRST_FIX_PROGRESSIVE	Checks whether the first fixation in the interest area is a first-pass fixation.
IA_FIRST_FIXATION_DURATION	Duration of the first fixation event that was within the current interest area
IA_FIRST_FIXATION_VISITED_IA_COUNT	This reports the number of different interest areas visited so far before the first fixation is made to the current interest area.
IA_FIRST_RUN_DWELL_TIME	Dwell time of the first run (i.e., the sum of the duration of all fixations in the first run of fixations within the current interest area).
IA_FIRST_RUN_FIXATION_COUNT	Number of all fixations in a trial falling in the first run of the current interest area.
IA_SKIP	An interest area is considered skipped (i.e., IA_SKIP = 1) if no fixation occurred in first-pass reading.
IA_TOP	Y coordinate of the top of the interest area.
IA_LEFT	X coordinate of the left-most part of the interest area.
normalized_Word_ID	Position in the paragraph of the word interest area, normalized from zero to one.
IA_REGRESSION_PATH_DURATION	The summed fixation duration from when the current interest area is first fixated until the eyes enter an interest area with a higher IA_ID.
IA_REGRESSION_OUT_COUNT	Number of times interest area was exited to a lower IA_ID (to the left in English) before a higher IA_ID was fixated in the trial.
IA_SELECTIVE_REGRESSION_PATH_DURATION	Duration of fixations and refixations of the current interest area before the eyes enter an interest area with a higher ID.
IA_LAST_FIXATION_DURATION	Duration of the last fixation event that was within the current interest area.
IA_LAST_RUN_DWELL_TIME	Dwell time of the last run (i.e., the sum of the duration of all fixations in the last run of fixations within the current interest area).
PARAGRAPH_RT	Reading time of the entire paragraph.
total_skip	Binary indicator whether the word was fixated on.
Fixation-level Eye Movement Features	
CURRENT_FIX_INDEX	The position of the current fixation in the trial.
CURRENT_FIX_DURATION	Duration of the current fixation.
CURRENT_FIX_PUPIL	Average pupil size during the current fixation.
CURRENT_FIX_X	X coordinate of the current fixation.
CURRENT_FIX_Y	Y coordinate of the current fixation.
NEXT_FIX_ANGLE, PREVIOUS_FIX_ANGLE	Angle between the horizontal plane and the line connecting the current fixation and the next/previous fixation.
NEXT_FIX_DISTANCE, PREVIOUS_FIX_DISTANCE	Distance between the current fixation and the next/previous fixation in degrees of visual angle.
NEXT_SAC_AMPLITUDE	Amplitude of the following saccade in degrees of visual angle.
NEXT_SAC_ANGLE	Angle between the horizontal plane and the direction of the next saccade.
NEXT_SAC_AVG_VELOCITY	Average velocity of the next saccade.
NEXT_SAC_DURATION	Duration of the next saccade in milliseconds.
NEXT_SAC_PEAK_VELOCITY	Peak values of gaze velocity (in visual degrees per second) of the next saccade.

Table 4: Word-level and fixation-level eye movement features.

Feature Name	Description
Surprisal	(Hale, 2001; Levy, 2008), formulated as $-\log_2(p(word\|context))$ for each *word* given the preceding textual content of the paragraph as *context*, probabilities extracted from the GPT-2-small language model (Radford et al., 2019; Wolf et al., 2020).
Wordfreq_Frequency	Frequency of the word based on the Wordfreq package (Speer, 2022), formulated as $-\log_2(p(word))$.
Length	Length of the word in characters.
start_of_line	Binary indicator of whether the word appeared at the beginning of a line.
end_of_line	Binary indicator of whether the word appeared at the end of a line.
Is_Content_Word	Binary indicator of whether the word is a content word. A content word is defined as a word that has a part-of-speech tag of either PROPN, NOUN, VERB, ADV, or ADJ.
n_Lefts	The number of leftward immediate children of the word in the syntactic dependency parse.
n_Rights	The number of rightward immediate children of the word in the syntactic dependency parse.
Distance2Head	The number of words to the syntactic head of the word.

Table 5: Linguistic word properties and their descriptions. POS tags and parse trees were obtained using SpaCy (Honnibal et al., 2020).

B Ablation Study

B.1 Backbone variants

Backbone	Gathering Trials				Hunting Trials			
	New Item	New Participant	New Item & Participant	All	New Item	New Participant	New Item & Participant	All
MAG (RoBERTa Large)	**54.8**	64.1	53.8	59.2	**52.5**	62.3	51.3	**57.1**
Frozen Backbone	54.3	61.4	51.4	57.5	51.9	60.0	**53.3**	55.8
+ trained on RACE	**54.8**	**64.6**	52.7	**59.3**	48.3	62.7	44.9	54.9
RoBERTa Base	52.8	64.0	**56.9**	58.3	50.8	**63.5***	51.6	56.9
PostFusion	54.8	**63.5**	55.0	**58.9**	**53.8**	**62.7**	53.8	**58.0**
Frozen Backbone	**55.5**	61.2	**55.1**	58.2	51.7	59.7	**54.1**	55.6

Table 6: Performance comparison of various backbone architectures and training strategies for MAG and PostFusion models on Hunting and Gathering trials. Results are presented for different generalization scenarios: New Item, New Participant, and New Item & Participant. The 'All' column represents overall performance across all conditions. Values indicate balanced accuracy scores. Statistically significant improvements compared to RoBERTa Large MAG (top) or PostFusion (bottom) are marked with '*' at $p < 0.05$, '**' at $p < 0.01$ and '***' at $p < 0.001$ using a paired bootstrap test. Unless stated otherwise, 'backbone' means RoBERTa Large.

B.2 The interaction of eye movements and linguistic word properties

MAG model input	Gathering Trials				Hunting Trials			
	New Item	New Participant	New Item & Participant	All	New Item	New Participant	New Item & Participant	All
Full (w Eyes & Ling. WP)	54.8	**64.1**	53.8	59.2	**52.5**	62.3	51.3	57.1
w/o Ling. WP	**55.9**	63.8	55.5	**59.6**	52.3	**63.3**	**54.8**	**57.7**
w/o Eyes	54.2	63.7	**56.7**	58.8	51.9	**63.3**	53.8	57.4
w/o Eyes & Ling. WP	54.8	63.1*	55.2	58.7	51.8	63.1	50.5	57.1

Table 7: Input ablations for the MAG model - the effect of removing the linguistic word property (WP) features, the eye movement features (as listed in Tables 4 and 5 respectively), or both on model performance. Results are presented for Hunting and Gathering trials across different generalization scenarios: New Item, New Participant, and New Item & Participant. The 'All' column represents overall aggregated performance across all three evaluations. Values indicate balanced accuracy scores. Statistically significant improvement of the **full model** over the ablated versions, using a paired bootstrap test, are marked with '*' at $p < 0.05$, '**' at $p < 0.01$ and '***' at $p < 0.001$.

C Hyperparameters

For model hyperparameter selection we follow best practice recommendations from Liu et al. (2019) and Mosbach et al. (2021). Models are trained with learning rates of $\{0.00001, 0.00003, 0.0001\}$ and dropout of $\{0.1, 0.3, 0.5\}$. For Eyettention and CNN , we also train with a learning rate of 0.001, as originally used in (Deng et al., 2023) (Ahn et al., 2020) accordingly. Following the same rational, for Eyettention we also use a dropout of 0.2.

For MAG-QEye we manipulate the injection layer index to be $\{0, 11, 23\}$.

For Logistic Regression, we train with the regularization parameter C with values of $\{0.1, 5, 10, 50, 100\}$, either applying L2 penalty or not, and with balanced class weighting or not. Feature scaling was performed using a standard scaler that normalizes features by removing the mean and scaling to unit variance.

For PostFusion-QEye the 1D convolution layers have a kernel size of three, stride 1, and padding 1,

Following (Reich et al., 2022), for BEyeLSTM we examine learning rates of $[0.001, 0.003, 0.01]$, and additionally embedding dimensions of $\{4, 8\}$ and hidden dimension of $\{64, 128\}$.

D Hardware and Software

All neural networks are trained using the Pytorch Lighting (Falcon and The PyTorch Lightning team, 2019) library, which builds upon Pytorch (Paszke et al., 2019), and evaluated using torch-metrics (Nicki Skafte Detlefsen et al., 2022) on a NVIDIA A100-40GB and A40-48GB GPUs. Normalization is done using Scikit-learn (Pedregosa et al., 2011). We adapt Huggingface's (Wolf et al., 2020) RoBERTa implementation. The baselines described in Section 5.5 are reimplemented in this framework as well. A single training epoch took approximately 5 minutes. We train for a maximum of ten epochs, stopping after three epochs without improvement.

The total number of model parameters, which is the same as the number of trainable parameters is 355M for the RoBERTa$_{\text{LARGE}}$ backbone, and an additional 1.1M for MAG-QEye and RoBERTa-QEye, and 9M for PostFusion-QEye.

E Baselines Modifications

First, for all models, we adapt the number of classes in the classification head according to Section 4. Model specific adaptations are as follows. Some models were originally designed to predict high versus low comprehension aggregated over multiple items. Here, we apply them at the level of individual items.

E.1 MAG

We replace the vision and acoustic input with word-level eye-movement features. To align them with the tokenized text we duplicate the word-level features for each subword token, as tokenized by the tokenizer. Additionally, for fair comparison we replace BERT with RoBERTa$_{\text{LARGE}}$ as the backbone model. We use dropout of 0.5, and fix the scaler parameter to 1e-3, as suggested by (Rahman et al., 2020).

Formally, each token embedding Z_i is *displaced* by H_i, for words in the paragraph.

$$\bar{Z}_i = Z_i + \alpha H_i \tag{4}$$

H_i is a scaled and transformed version of the eye movements E_i,

$$H_i = g_i \cdot (W_e E_i) + b_H \tag{5}$$

where the scaling is defined by,

$$g_i = ReLU(W_g[Z_i; A_i] + b_g) \tag{6}$$

The amount of displacement is defined by

$$\alpha = min(\frac{||Z_i||_2}{||H_i||_2}\beta, 1) \tag{7}$$

where β is a hyper-parameter, and W_e, W_g, b_H, b_g are learned.

Finally, the contextualized CLS token is used for classification, with a binary classification head outputting the prediction score.

E.2 Eyettention

Due to the difference between trial (ours) and fixation (Deng et al. (2023)) predictions, we use global cross attention between the word sequence and the scanpath sequence instead of fixed window cross attention, both of which were suggested in Deng et al. (2023). We then represent the whole scanpath using a single vector, which is the last hidden representation of the scanpath LSTM. Differently from the original model which uses BERT, we use RoBERTa Large for consistency with the other models.

BEyeLSTM - Firstly, we employ SpaCy tokenization based on paragraph-level input rather than word-level input, resulting in more precise tokenization. Secondly, the textual materials used here include a greater number of part of speech tags and entities, which expands the final feature set. Lastly, we omit the "words in fixed context on unigrams" feature, as it presumes that all participants read the same text, which is not the case in OneStop.

CNN - Ahn et al. (2020) resort to artificially subdividing SB-SAT texts into smaller segments in order generate a sufficient number of training examples to make the dataset usable for their task of predicting low versus high comprehension over multiple items. This heuristic is problematic in general, and not applicable to the single item task addressed here. Thus, we use as input the whole fixation sequence.

F Cross Validation Splits

The splits result in seventy-two participants in each participant fold (thirty-six from each reading condition), and six articles in each item fold. Each split further guarantees an equal number of participants from each OneStopQA batch in each data portion, and is approximately stratified by answer type. Note that each participant is presented with a specific combination of a paragraph and one of three associated questions. Participants are divided into folds in a way that does not guarantee an equal distribution of each question across the *participant* folds. Further, note that each participant and each item appear in a test fold once, but not all appear in each evaluation regime, as this would require $k_i \cdot k_p$ data splits for k_i item and k_p participant folds.

G Validation Results

The following are results on the validation sets.

Binary Reading Comprehension			Ordinary Reading (Gathering)				Information Seeking (Hunting)			
Model	Gaze Representation	Text Representation	New Item	New Participant	New Item & Participant	All	New Item	New Participant	New Item & Participant	All
Majority	None	None	50.0	50.0	50.0	50.0	50.0	50.0	50.0	50.0
Text-only RoBERTa	None	Emb	59.8	**65.8**	57.9	62.5	57.1	65.1	56.8	60.8
Log. Reg. (Mézière et al., 2023b)	Global	None	53.4	51.1	53.9	52.3	51.8	53.0	51.9	52.4
CNN (Ahn et al., 2020)	Fixations	None	53.3	53.7	53.4	53.5	55.1	54.5	55.0	54.8
BEyeLSTM (Reich et al., 2022)	Fixations	Ling. Feat.	55.0	58.5	55.7	56.7	57.3	58.6	58.3	58.0
Eyettention (Deng et al., 2023)	Fixations	Emb + Word Len.	58.5	62.4	57.9	60.3	57.0	59.5	56.9	58.2
RoberteyeWord	Words	Emb + Ling. Feat.	57.0	65.5	**60.5**	61.2	55.3	64.7	52.2	59.6
RoBERTeyeFixation	Fixations	Emb + Ling. Feat.	57.0	63.5	60.4	60.3	54.6	62.4	56.5	58.4
MAG	Words	Emb + Ling. Feat.	**60.4**	**65.8**	58.9	**62.9**	57.3	**66.0**	**59.5**	61.6
PostFusion	Fixations	Emb + Ling. Feat.	60.1	65.2	60.4	62.5	**58.3**	65.8	59.3	**61.9**

Table 8: Balanced accuracy for the main binary reading comprehension prediction task (correct vs incorrect comprehension) on OneStop. Evaluations are presented in ordinary reading and information seeking, for previously unseen items, participants, or both. 'All' denotes results for the aggregation of all the trials across the three validation regimes. 'Emb' stands for word embeddings, 'Ling. Feat.' for linguistic word properties.

Multiple-Choice Reading Comprehension			Ordinary Reading (Gathering)				Information Seeking (Hunting)			
Model	Gaze Representation	Text Representation	New Item	New Participant	New Item & Participant	All	New Item	New Participant	New Item & Participant	All
Majority	None	None	25.0	25.0	25.0	25.0	25.0	25.0	25.0	25.0
Text-only RoBERTa	None	Emb	25.7	35.7	25.6	30.4	25.0	**34.4**	25.5	29.5
MAG	Words	Emb + Ling. Feat.	**33.8**	**36.1**	**34.3**	**34.9**	**34.8**	33.6	32.9	**34.1**
PostFusion	Fixations	Emb + Ling. Feat.	33.2	35.1	33.5	34.1	34.0	31.8	**35.4**	33.0

Table 9: Balanced accuracy for the multiple-choice specific answer prediction task on OneStop, with MAG and PostFusion, the best performing models in the ordinary reading and information seeking regimes on the main task, respectively (see Table 2).