

Can LLMs Estimate Cognitive Complexity of Reading Comprehension Items?

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Abstract

Estimating the cognitive complexity of reading comprehension (RC) items is crucial for assessing item difficulty before it is administered to learners. Unlike syntactic and semantic features, such as passage length or semantic similarity between options, cognitive features that arise during answer reasoning are not readily extractable using existing NLP tools and have traditionally relied on human annotation. In this study, we examine whether large language models (LLMs) can estimate the cognitive complexity of RC items by focusing on two dimensions—Evidence Scope and Transformation Level—that indicate the degree of cognitive burden involved in reasoning about the answer. Our experimental results demonstrate that LLMs can approximate the cognitive complexity of items, indicating their potential as tools for prior difficulty analysis. Further analysis reveals a gap between LLMs’ reasoning ability and their metacognitive awareness: even when they produce correct answers, they sometimes fail to correctly identify the features underlying their own reasoning process.

1 Introduction

Estimating the difficulty of reading comprehension (RC) items¹ is essential for delivering appropriate learning materials and constructing balanced test forms. Traditionally, difficulty has been derived from student responses using frameworks such as classical test theory (CTT) or item response theory (IRT) (Lord, 1980; Hambleton and Jones, 1993). However, these approaches are only applicable after test administration and thus cannot support prior difficulty prediction during item development. Expert judgment remains the common alternative, but it is costly, time-consuming, and subject to rater variability (AlKhuzaey et al., 2024).

¹An RC item typically consists of a passage, a question stem, and sometimes answer options (in the case of the multiple-choice format). In this paper, we use the term “item” interchangeably with “question.”

Passage

- (1) Mia loved baking and often spent her weekends experimenting with new recipes.
- (2) Her specialty was a chocolate cake that her family couldn't get enough of.
- (3) Every Sunday afternoon, the smell of cocoa and vanilla would fill the house.
- (4) Her younger brother, Sam, always asked for a second slice.
- (5) One weekend, Mia decided to enter the local baking competition.
- (6) She worked hard all week preparing the perfect version of her cake.
- (7) The judges praised the moist texture and rich flavor, and Mia won first place.
- (8) After the win, she was invited to share her recipe in the local newspaper.
- (9) Although she was nervous, she accepted the invitation and was excited to see her name in print.
- (10) Mia started thinking about attending a culinary school in the future.

Statement	Evidence Scope & Transformation Level
Mia's specialty was a chocolate cake.	Single-sentence evidence (s1) Word Matching
Mia's house would be filled with the smell of cocoa and vanilla every Sunday afternoon.	Single-sentence evidence (s3) Transformed Word Matching
Despite feeling nervous, Mia was thrilled to have her name published.	Single-sentence evidence (s9) Paraphrasing
Mia received an invitation to publish her recipe in the newspaper following her victory.	Single-sentence evidence (s8) Transformed Paraphrasing
Mia's cake was better than the other contestants' cakes.	Single-sentence evidence (s7) Inference
Mia loved baking and won first place.	Multi-sentence evidence (s1&s7) Word Matching
Mia regularly tried new recipes on weekends and chose to join a baking contest.	Multi-sentence evidence (s1&s5) Paraphrasing
Mia's success in the contest encouraged her to consider becoming a professional baker.	Multi-sentence evidence (s7&s10) Inference
Sam wanted to learn baking from her.	Insufficient evidence

Figure 1: Examples of RC items that require determining the factuality of a statement. Each item is annotated along two cognitively grounded dimensions (*Evidence Scope* and *Transformation Level*) with corresponding supporting sentences highlighted from the passage.

To address this limitation, prior work has explored item features correlated with difficulty and employed them for prediction (Pandarova et al., 2019; Choi and Moon, 2020; Benedetto et al., 2021). These include syntactic, semantic, and psycholinguistic variables (e.g., sentence length, semantic similarity between options, and word familiarity), which can be extracted using NLP tools such as Coh-Metrix (McNamara et al., 2014) or embedding models like BERT (Devlin et al., 2019). Yet such surface-level features provide limited insight into the reasoning processes that largely govern difficulty.

Educational psychology research has shown that cognitive factors involved in the answer decision

process are more strongly associated with difficulty (Embreton and Wetzel, 1987). Examples include the amount of text that must be referenced to determine the correct answer and the degree of transformation between passage evidence and the answer (Bormuth et al., 1970; Anderson, 1972). However, these cognitive features cannot be automatically extracted with existing NLP tools, and prior studies have relied exclusively on human raters (Hutzler et al., 2014; Lai et al., 2017). This raises a key challenge: *How can we estimate the cognitive complexity of RC items in a scalable way?*

We believe that large language models (LLMs), with their powerful reasoning and instruction-following capabilities, may offer a promising approach to this problem. Recent studies have attempted to leverage LLMs for estimating question difficulty. However, many of these efforts have focused on tasks solvable solely through a model’s internal knowledge—such as mathematics and coding (Rogoz and Ionescu, 2024; Park et al., 2024; Ko et al., 2024; Xu et al., 2024)—or have directly prompted LLMs to predict the difficulty of RC items (Raina and Gales, 2024). Whether LLMs can meaningfully analyze the cognitive complexity involved in solving RC items, however, remains largely unexplored.

Motivated by this gap, we investigate LLMs’ capability to measure the complexity of two cognitive variables: **Evidence Scope** and **Transformation Level**. Evidence Scope reflects the amount of text required to verify an answer—categorized as single-sentence, multi-sentence, or insufficient—while Transformation Level captures the degree of lexical and structural transformation between an option and its supporting evidence in the passage, ranging from word matching to inference. To support empirical evaluation, we constructed a benchmark dataset, **RECo**, which comprises 776 RC items annotated along these two cognitive dimensions (see Figure 1). Of the whole dataset, 498 items are allocated to the test set, with the remainder reserved for prompting demonstrations.

In our experiments, we evaluate eight LLMs, spanning both proprietary and open-source variants. The results show that LLMs can approximate cognitive complexity, with the best-performing models achieving F1 scores of 75.5 (Evidence Scope) and 83.2 (3-level Transformation Level) in the cognitive complexity classification tasks. Notably, open-source models such as Qwen2.5 (32B) and Mistral-Small (24B) performed comparably to—or even

surpassed—GPT-4o. However, we also found that LLMs often struggle to explicitly recognize key features in their reasoning traces—for example, identifying phrase reordering or the evidence sentences they referenced—highlighting a gap between reasoning ability and metacognitive awareness.

Our contributions can be summarized as follows:

- We construct an expert-annotated dataset of RC items along two cognitively grounded dimensions, which are important factors for analyzing item difficulty².
- We conduct an evaluation of eight instruction-tuned LLMs, demonstrating their potential utility in estimating the cognitive complexity of RC items.
- We probe LLMs on fine-grained cognitive features and observe that, even when they successfully solve items, they do not fully recognize the cognitive processes underlying their problem solving.

2 Related Work

2.1 Difficulty Factors and Taxonomies

Research in educational psychology has long examined the factors influencing RC item difficulty (Bormuth et al., 1970; Anderson, 1972; Freedle and Kostin, 1991; Park, 2004; Rafatbakhsh and Ahmadi, 2023). Researchers have sought to identify correlations between item-based attributes—such as surface-level linguistic features (e.g., sentence complexity, vocabulary difficulty) and cognitive burden factors (e.g., plausibility of distractors, option–text mapping)—and item difficulty, often measured using CTT or IRT (Hsu et al., 2018; Pandarova et al., 2019; Choi and Moon, 2020; Zhou and Tao, 2020; Benedetto et al., 2021). More recently, tools such as Coh-Metrix (McNamara et al., 2014), NLTK (Loper and Bird, 2002), and embedding models like Word2Vec (Mikolov et al., 2013) or BERT (Devlin et al., 2019) enable the automatic extraction of syntactic and semantic features. These features have been used as inputs to supervised models such as linear regression for difficulty prediction.

Several taxonomies have been proposed to systematically classify the complexity of RC items. Bloom’s taxonomy, for instance, organizes learning objectives by levels of cognitive demand (Bloom et al., 1956). Lai et al. (2017) employed a five-

²The dataset, prompt templates, and evaluation codes are available at <https://github.com/SeonjeongHwang/ReCo>

level taxonomy to characterize reasoning across RC items, which is a simplified combination of the two dimensions adopted in our study. While previous taxonomies have been used to categorize different types of RC items—such as main idea, author’s intent, fill-in-the-blank, and detail information questions—our study focuses on distinguishing variations in cognitive complexity, even within items of the same type.

2.2 LLM-based Difficulty Estimation

Recently, various approaches have been proposed to leverage LLMs for predicting item difficulty. Some studies directly prompted LLMs to estimate difficulty (Xu et al., 2024), while others inferred difficulty from model-generated outcomes such as answering accuracy or confidence scores (Rogoz and Ionescu, 2024; Park et al., 2024; Lu and Wang, 2024; Jain et al., 2025). However, much of this prior work has focused on domains such as mathematics, medicine, or coding, where models rely solely on their internal knowledge to solve the problems. This differs from RC, where the model must reference the information provided in the passage while applying its own reasoning ability.

Several studies have explored LLMs for predicting RC item difficulty. Raina and Gales (2024) found that comparative prompting—asking an LLM to compare the relative difficulty of two items—aligned better with human judgments than absolute prompting, where the model assigns a difficulty score to a single item. Dutulescu et al. (2024) predicted item difficulty using indicators derived from LLMs’ question answering (QA) loss. Kapoor et al. (2025) showed that combining item text features, LLM embeddings, and contextual information (e.g., grade level, year) improved prediction performance, underscoring the importance of item-feature-based analyses. Instead of directly predicting item difficulty, this paper investigates whether LLMs can estimate two cognitively grounded features that influence difficulty.

2.3 Datasets

While QA datasets such as SQuAD (Rajpurkar et al., 2016) and BoolQ (Clark et al., 2019) are widely used, they lack per-item difficulty annotations, limiting their usefulness for difficulty analysis. RACE++ (Lai et al., 2017; Liang et al., 2019) contains RC items spanning middle school through college levels and has been used with grade level as a proxy for difficulty (Raina and

Gales, 2024; Liusie et al., 2023), but this approach does not capture fine-grained variation within a single learner group. Multi-hop QA datasets such as HotpotQA (Yang et al., 2018) assess complexity through multi-hop reasoning across documents, yet this setup differs from standard RC formats in educational assessment, which typically involve a single reading passage.

Huang et al. (2017) predicted item difficulty using student error rates on English reading problems in China, but the full dataset was not released. Mullooly et al. (2023) released the CMCQRD dataset, which contains 289 RC items labeled with CEFR levels and IRT-based difficulty scores derived from pretesting, providing holistic estimates of item difficulty. Dutulescu et al. (2024) annotated FairytaleQA (Xu et al., 2022) along two dimensions: explicit vs. implicit and local vs. summary. This dataset is the closest to our ours, but the two dimensions considered in this work capture more fine-grained cognitive features involved in the answer decision process of RC items.

3 Data Construction

To construct our dataset, we used True/False/Not Given (TFNG) items, where the task is to assess the factuality of a statement given a passage. Each item comprises a reading passage and a declarative statement, as illustrated in Figure 1. This format is particularly suitable for our study, as it spans a wide range of cognitive complexity—from direct span matching to multi-sentence inference—and is commonly featured in the RC sections of standardized proficiency exams.

3.1 Dimensions of Cognitive Complexity

Evidence Scope. Items that can be solved by referencing a single sentence in the passage are generally easier than those requiring integration of information scattered across multiple sentences (Bormuth et al., 1970; Park, 2004). In this study, Evidence Scope refers to the span of text required to determine the truth value of a statement, and is categorized into three levels:

- **Single-sentence evidence:** All necessary information to evaluate the statement is contained within a single sentence in the passage.
- **Multi-sentence evidence:** The required information is distributed across multiple sentences (i.e., inter-sentence comprehension).
- **Insufficient evidence:** The passage lacks ad-

equate information to definitively confirm or refute the statement. In such cases, learners are required to examine the entire passage before concluding that the passage provides no supporting evidence.

A special case arises when the supporting evidence includes anaphoric expressions. While [Bormuth et al. \(1970\)](#) treated such items as a separate category, they found little difference in difficulty compared to single-sentence evidence. Accordingly, we apply the following rules: 1) If the anaphora clearly refers to a frequently mentioned and easily identifiable entity in the prior sentences, the item is classified as single-sentence evidence. 2) However, if resolving the anaphora requires referring back to a prior sentence, we label it as multi-sentence evidence. This approach reflects that many reading passages in RC assessments employ anaphoric references, and accounting for such subtleties is essential for accurate difficulty prediction.

Transformation Level. When the degree of transformation between a statement and its supporting evidence is higher, identifying the corresponding passage text and assessing the statement’s truth value imposes greater cognitive demands ([Bormuth et al., 1970](#); [Anderson, 1972](#)). We adopt a *5-level* taxonomy inspired by previous work, which captures the type of transformation required to derive a statement from the evidence:

- **Word Matching:** The content words in the statement appear verbatim in the evidence, and the phrase order is preserved.
- **Transformed Word Matching:** The content words are still present in the evidence but have been rearranged.
- **Paraphrasing:** The statement rephrases the content words without changing the order of the words.
- **Transformed Paraphrasing:** The content words are rephrased and the phrase order is altered, combining lexical and structural transformation.
- **Inference:** The statement cannot be directly derived from any surface form in the passage, even through paraphrasing or reordering; instead, it requires inference.

In contrast to the *single-sentence evidence* cases, phrase reordering is either trivial or pervasive in *multi-sentence* cases; therefore, we label these items using a simplified *3-level* taxonomy: *word matching*, *paraphrasing*, and *inference*. In addition,

anaphora resolution, identifying the antecedent of an anaphor within a text, is not considered paraphrasing unless additional lexical transformation is involved.

3.2 Data Annotation

We collected TFNG items from multiple-choice True/False questions in the RACE++ dataset ([Lai et al., 2017](#); [Liang et al., 2019](#)), which comprises English RC exams administered at the middle school, high school, and college levels in China. Each item consists of a passage, a statement, and its binary factuality label (*True* or *Not True*).

To ensure reliable annotation, we recruited three experts via Upwork³, each with prior experience tutoring for standardized English exams or authoring RC items. The annotators independently identified the evidence sentences in the passage, and labeled each item along the two cognitive dimensions. For statements identified as *False* within the *Not True* cases, they produced minimally revised *True* statements to enable annotation of transformation level. We retained only items where at least two annotators agreed on the same label; in cases of partial agreement, discrepancies were resolved through author adjudication. The resulting annotated dataset, which we refer to as RECO, is released for non-commercial research purposes under the RACE license. Further details on the annotation process and inter-annotator agreement are provided in Appendix A.

3.3 Data Statistics

Table 1 summarizes the distribution of items across labels. For Evidence Scope, 50% items are labeled as single-sentence evidence, while insufficient evidence items account for the lowest proportion. For Transformation Level, items requiring inference are the most frequent, whereas transformed word matching items are the least common. In the 3-level scheme, which includes multi-sentence comprehension items, inference items remain dominant. These statistics reveal an imbalanced label distribution in our dataset. This imbalance is expected, since the items originate from real exams, and the distributions may vary across tests designed for different proficiency levels or languages. Further analysis of our dataset can be found in Appendix B.

³<https://www.upwork.com>

Evidence Scope	
Single-sentence Evidence	388
Multi-sentence Evidence	243
Insufficient Evidence	145
Transformation Level	
5-level	3-level
Word Matching	73
Transformed Word Matching	36
Paraphrasing	55
Transformed Paraphrasing	78
Inference	146
	Word Matching 123
	Paraphrasing 189
	Inference 319

Table 1: Distribution of examples in the RECO dataset across Evidence Scope and Transformation Level. For the Transformation Level dimension, items labeled as insufficient evidence are excluded, and the 5-level scheme applies only to single-sentence comprehension items.

4 Experimental Setup

We formulate the measurement of cognitive complexity as a classification task. In the **Evidence Scope (ES) classification**, the model receives an instruction, a passage, a statement, and its factuality label (*True* or *Not True*), and predicts one of three evidence types: *single*, *multi*, or *insufficient*. In the **Transformation Level (TL) classification**, applied to items with *True* statements, the model estimates the degree of transformation using the task definition, passage, and statement. We report performance using both the 5-level taxonomy—*word matching* (*WM*), *transformed word matching* (*TWM*), *paraphrasing* (*P*), *transformed paraphrasing* (*TP*), and *inference* (*I*)—and a simplified 3-level version (*WM*, *P*, *I*), which omits distinctions based on phrase reordering. In the 3-level setting, predictions of *TWM* and *TP* are mapped to *WM* and *P*, respectively, and ground-truth labels for single-sentence evidence items are converted accordingly. Model performance is measured using the micro-averaged F1 score.

We evaluate eight *instruction-tuned* LLMs, including open-source models Gemma2-9B/27B (Team, 2024a), Mistral-7B/24B (Jiang et al., 2023), and Qwen2.5-7B/32B (Team, 2024b), as well as proprietary models GPT-4o and GPT-4o-mini (Hurst et al., 2024). Two prompting strategies are considered: Standard Prompting (SP), where the model receives a task definition and input and returns a label directly; and Chain-of-Thought Prompting (CoT), which encourages step-by-step reasoning before prediction (Wei et al., 2022). Greedy decoding is used as the default in-

ference method across all models and prompting strategies. In the CoT setting, we additionally apply self-consistency decoding (Wang et al., 2022), generating 10 samples with top- $k=20$, top- $p=0.8$, and temperature=0.7 and using priority answer.

Each strategy is evaluated under three prompting conditions—zero-shot, one-shot, and few-shot (Brown et al., 2020)—with the few-shot demonstrations covering items from all labels. Exemplars are sampled from the RECO demonstration split and fixed across models to ensure consistency. To filter out overly trivial items that might inflate model performance, we exclude those that GPT-4o correctly classifies with a zero-shot CoT prompt. Details on model versions and the experimental environment are provided in Appendix C.

5 Results

Table 2 presents the performance of LLMs and human experts on the ES and TL classification tasks. Human performance is computed using annotators’ initial labels, before applying inter-annotator agreement filtering and adjudication. The table also reports LLMs’ performance on the RC task, which requires the model to determine whether a statement is true or not based on the passage.

Before evaluating LLMs’ ability to analyze the cognitive complexity, we first examined their performance on the RC task itself. According to the results, all models except the Mistral family achieved F1 scores above 80, with larger models approaching 90, indicating strong reading comprehension ability. This result confirms that the RC items in the RECO dataset are relatively easy for current LLMs, and thus that errors in cognitive complexity prediction are unlikely to stem from failures in basic comprehension or answer reasoning. However, for smaller models such as Mistral-7B, incomplete comprehension may still contribute to some degree of performance variation.

In the ES classification task, GPT-4o achieves the highest F1 score (75.5) with a one-shot CoT prompt, and Qwen2.5-32B performs comparably (73.1). Yet all models fall short of expert performance (87.9), highlighting the difficulty of modeling human cognitive processes in evidence selection. Within open-source model families, larger models tend to yield comparable performance across variants—particularly under self-consistency decoding—, while smaller models exhibit more divergent results. Mistral-7B, in par-

Method	#Demo	Gemma2 9B	Mistral 27B	Mistral 7B	Qwen2.5 24B	Qwen2.5 7B	GPT-4o 32B	GPT-4o mini	-
<i>Reading Comprehension</i>									
CoT	1	85.1	89.2	63.7	79.7	80.9	88.2	87.0	89.4
<i>Evidence Scope Classification [Human: 87.9]</i>									
SP	0	48.8	55.2	43.0	58.8	46.0	56.4	51.8	57.8
	1	48.8	<u>60.0</u>	45.8	<u>59.8</u>	49.8	<u>59.8</u>	<u>55.2</u>	60.8
	6	50.4	53.6	49.4	57.0	<u>51.8</u>	58.4	54.6	<u>65.7</u>
CoT	0	60.0	62.7	21.3	63.7	59.2	70.5	66.3	72.5
	1	<u>64.5</u>	<u>70.1</u>	53.6	66.3	58.4	73.1	<u>68.9</u>	75.5
	6	62.9	69.1	<u>55.6</u>	<u>68.5</u>	<u>60.6</u>	70.7	66.7	69.5
CoT (SC)	0	61.7	67.9	19.5	68.3	60.4	73.1	67.3	72.9
	1	67.7	72.3	57.8	71.1	61.9	72.9	72.3	74.1
	6	63.9	70.7	56.6	68.9	60.8	71.5	69.3	72.9
<i>(3-level) Transformation Level Classification [Human: 85.9]</i>									
SP	0	57.9	55.9	46.8	73.7	62.4	67.5	67.0	70.7
	1	55.2	58.3	<u>58.4</u>	<u>75.4</u>	58.8	69.0	67.8	69.7
	8	<u>58.3</u>	64.3	55.7	73.5	54.7	60.0	59.4	64.9
CoT	0	53.1	58.8	59.0	76.9	68.6	72.4	67.8	76.6
	1	50.9	56.8	48.6	<u>75.2</u>	76.2	<u>74.7</u>	71.9	78.1
	8	<u>57.1</u>	<u>61.3</u>	<u>62.8</u>	75.4	66.0	73.2	73.6	75.4
CoT (SC)	0	58.6	54.6	68.5	83.2	76.5	78.3	69.6	74.1
	1	54.6	58.0	52.2	67.9	72.3	76.2	<u>71.5</u>	<u>74.3</u>
	8	64.2	<u>62.7</u>	64.1	76.9	66.8	73.3	71.4	71.8
<i>(5-level) Transformation Level Classification [Human: 83.5]</i>									
SP	0	36.8	38.8	28.4	52.0	43.6	51.2	51.2	<u>54.8</u>
	1	<u>42.0</u>	42.4	34.0	<u>57.2</u>	<u>47.6</u>	<u>52.0</u>	<u>50.8</u>	52.8
	8	<u>35.6</u>	49.6	<u>40.0</u>	56.4	42.8	43.2	48.8	52.4
CoT	0	34.0	43.2	38.8	<u>59.2</u>	42.8	<u>59.6</u>	52.8	66.0
	1	37.6	38.4	32.0	54.0	<u>53.6</u>	58.4	56.0	67.2
	8	42.8	<u>47.6</u>	<u>48.0</u>	56.4	48.0	55.6	58.8	59.2
CoT (SC)	0	37.6	44.0	44.8	67.2	46.0	66.0	54.8	60.4
	1	43.2	45.2	39.2	53.6	56.8	63.2	55.6	<u>63.6</u>
	8	48.0	<u>48.4</u>	50.0	58.8	45.2	59.2	56.4	58.8

Table 2: Performance of LLMs on the RC task and the ES and TL classification tasks. Greedy decoding is the default inference method, and SC indicates that self-consistency decoding is used. **Bolded** values denote each model’s best score per task; underlined values indicate the best score across demonstration settings.

ticular, exhibits unstable behavior, occasionally yielding unexpectedly low scores despite identical prompts. As expected, zero-shot prompting underperforms compared to demonstration-based settings. However, in large models, few-shot prompting occasionally degraded performance, likely due to longer context length overwhelming their attention capacity.

In the TL classification task with the 3-level taxonomy, Mistral-24B (83.2) and Qwen2.5-32B (78.3) outperform GPT-4o (78.1), approaching human performance (85.9). Under the 5-level taxonomy, however, overall model performance decreases, underscoring the challenge of capturing phrase reordering between statements and evidence. Nevertheless, open-source models again achieve

performance comparable to GPT-4o. By contrast, Gemma2-27B consistently underperforms, trailing even smaller models, which suggests limitations in handling lexical and syntactic transformations. Prompting effects are less consistent than in ES classification: optimal configurations vary by model, and in some cases zero-shot prompting even outperforms demonstration-based prompting. Self-consistency decoding improves results in several settings, particularly zero-shot CoT, but its gains are less stable than in ES classification.

In summary, while LLMs do not fully align with expert judgments, they demonstrate strong potential as estimators of cognitive complexity in RC items, especially in ES and 3-level TL classifications. Notably, the competitive performance of open-source models relative to GPT-4o suggests that reliance on proprietary LLMs may not be necessary for analyzing cognitive complexity. While we employ simple prompting methods to better isolate inherent model capabilities, more advanced prompt engineering may yield further improvements. In Appendix D, we evaluate the reasoning-specialized model Qwen3 (Team, 2025).

6 Analysis

6.1 Fine-Grained Feature Analysis

To better understand the capabilities and limitations of LLMs, we decomposed the two classification tasks into a set of fine-grained sub-tasks. For each sub-task, we constructed few-shot CoT prompts by adapting those used in the main experiments, with instructions tailored to the specific cognitive feature under evaluation. Results are reported in Table 3.

The ES classification task was divided into two core sub-tasks: **Sub-task 1.1: Falsifiability Judgment** – determining whether a *Not True* statement is *False* (contradicted) or *Not Given* (lacking sufficient evidence). **Sub-task 1.2: Evidence Sentence Counting** – identifying how many sentences are required to support or refute a statement. Most models performed reliably on falsifiability classification, but performance was substantially lower for evidence sentence counting. This suggests that while LLMs can distinguish between refuted and unsupported statements, they struggle to explicitly identify all sentences that humans reference when solving the item.

The TL classification task was evaluated through a hierarchical breakdown of transformation types,

Sub-task	Gemma2 9B	Mistral 27B	Qwen2.5 7B	GPT-4o mini	-
(1.1)	82.8	82.1	71.4	81.7	77.5
(1.2)	68.7	74.3	59.2	69.4	68.5
(2.1)	73.4	75.8	65.5	82.4	68.7
(2.2)	81.9	84.9	67.3	85.9	72.4
(2.3)	59.5	68.0	58.8	61.4	51.0
					54.3
					66.7
					65.4

Table 3: LLM performance on sub-tasks measuring fine-grained abilities required for the main classification tasks. **Bold** values denote the best model for each sub-task.

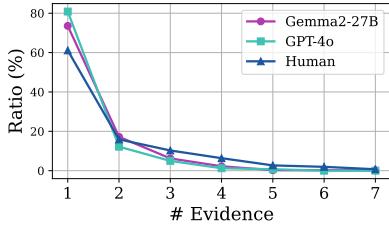


Figure 2: Distribution of the number of evidence sentences selected by LLMs and humans.

allowing for a more detailed examination of how LLMs handle different forms of linguistic transformation: **Sub-task 2.1. Inference Detection** – distinguishing inference-based statements from those explainable by surface-level transformations, such as paraphrasing or phrase reordering. **Sub-task 2.2. Paraphrasing Detection** – identifying whether a statement is a lexical rephrasing or a verbatim restatement. **Sub-task 2.3: Phrase Reordering Detection** – detecting reordering of words and phrases. According to the results, model performance showed distinct strengths and weaknesses across sub-tasks. GPT-4o-mini performed comparably to, or even better than, GPT-4o—especially on inference and phrase reordering detection, where GPT-4o underperformed. Paraphrasing detection was handled well across models, while phrase reordering remained especially challenging.

Overall, LLMs showed consistent performance on falsifiability classification (Sub-task 1.1) and paraphrase detection (Sub-task 2.2), but struggled with evidence sentence counting (Sub-task 1.2) and phrase reordering detection (Sub-task 2.3). While models demonstrated strong answer reasoning ability (as shown in Table 2), our analysis indicates that even when they solved items correctly, they often failed to explicitly capture the cognitive features underlying their reasoning process.

Evidence Selection	Precision	Recall	F1
Gemma2-27B	86.4	78.3	78.8
Mistral-24B	82.4	74.4	74.3
Qwen2.5-32B	85.4	76.9	77.4
GPT-4o	88.8	79.2	80.0

Table 4: Model performance on evidence sentence selection.

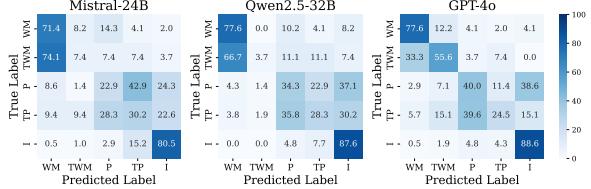


Figure 3: Distribution of TL labels predicted by LLMs for single-sentence evidence items.

6.2 Error Analysis

We further examined the prediction tendencies of GPT-4o and the best-performing model in each task. Figure 2 shows the distribution of the number of evidence sentences predicted by Gemma2-27B and GPT-4o, compared to human-selected evidence. LLMs tend to select fewer sentences than humans, often defaulting to a single sentence as evidence. Table 4 reports the degree of alignment between the evidence sentences selected by each model and those identified by experts. As in the previous observation, recall scores were consistently lower than corresponding precision scores, indicating that models often fail to explicitly retrieve all the sentences required by humans to solve the item. We hypothesize that LLMs—by encoding the entire passage before engaging in step-by-step reasoning—tend to overlook sentences containing seemingly minor details that nevertheless exert a significant influence on the answer choice, remaining unaware of these omissions.

Figure 3 presents the distribution of TL predictions for items with *single-sentence evidence*. LLMs consistently achieved higher precision for *WM* and *I* items than for other categories. However, they frequently misclassified *TWM* as *WM*, failing to detect subtle reordering of phrases. Models also showed confusion between *P* and *TP*, often misclassifying them as each other or as *I*. These patterns align with the earlier results in Table 3, particularly for phrase reordering detection, where all models struggled. Representative error cases illustrating these confusions are analyzed in the next

<i>Case #1</i>	
Passage: (1) Once upon a time, there was an island where all the feelings lived: Happiness, Sadness, Knowledge, and all of the others, including Love. (...) (15) Sadness was close by so Love asked, “Sadness, let me go with you.” (16) “Oh...Love, I am so sad that I need to be by myself!” (17) Happiness passed by Love, too, but she was so happy that she did not even hear when Love called her. ... Statement: Sadness wanted to stay alone. Ground Truth ES: Multi-sentence evidence	GPT-4o’s Response: 1. Understand the Statement - Statement: “Sadness wanted to stay alone.” - Key claim: Sadness had a desire to be alone. 2. Retrieve Relevant Information from the Passage - Sentence (15): Love asks Sadness if she can go with her. - Sentence (16): Sadness responds, “Oh...Love, I am so sad that I need to be by myself!” 3. Assess Scope of Evidence - Sentence (16) directly supports the statement by indicating Sadness’s desire to be alone. - <u>The sentence explicitly mentions Sadness’s need to be by herself</u> , which aligns with the statement that Sadness wanted to stay alone. (...) Answer: Single
Passage: (1) Detective Wolf and Miss Fox (2) Detective Wolf has waited in the doorway all the morning. (3) He is going to meet Miss Fox. (4) She bought a bag of diamonds from Africa. (...) Statement: The diamonds were bought from Africa. Ground Truth TL: Transformed Word Matching	Case #2 GPT-4o’s Response: 1. Analyze the Statement - Content words: diamonds, bought, Africa 2. Locate Supporting Evidence in the Passage - Sentence (4): “She bought a bag of diamonds from Africa.” 3. Compare the Statement and Evidence - All content words match exactly with the passage: “diamonds,” “bought,” “Africa.” - <u>The order of content words is exactly the same as in the statement.</u> (...) Answer: Word Matching

Figure 4: Representative error cases with GPT-4o’s responses.

subsection.

6.3 Case Study

Figure 4 presents error cases that illustrate common failure patterns in LLMs. We analyze two examples where GPT-4o incorrectly classifies items in the ES and TL classification tasks. In Case #1, the model misclassifies an item requiring *multi-sentence evidence* as *single-sentence evidence*. The passage involves multiple characters in dialogue, and correctly identifying the speaker of a specific utterance is essential for determining the truth of the statement. According to annotators, both Sentence (15) and Sentence (16) are required: Sentence (15) establishes that the subject is “Sadness,” while Sentence (16) describes her action. However, the model references Sentence (15) in its explanation and correctly links “Sadness” to the action in Sentence (16), yet asserts: “Sentence (16) explicitly mentions Sadness’s need to be by herself.” The case reveals a metacognitive failure: the model arrives at the correct factual judgment but fails to recognize the reasoning behavior it engaged in to reach that conclusion.

In Case #2, the item labeled as *TWM* was incorrectly classified as *WM*. A comparison with Sentence (4) reveals a reordering of content words caused by a shift to the passive construction. However, GPT-4o claims: “The order of content words in the evidence is exactly the same as in the statement.” This suggests that the model sometimes fails to detect subtle syntactic transformations. These two cases together suggest that, even when LLMs provide seemingly coherent explanations, they may miss structural cues and fail to reflect on the rea-

soning processes underlying their own answers. Such blind spots underscore a persistent challenge of detecting and modeling the cognitive features underlying human problem-solving processes.

7 Conclusion

The cognitive complexity of the problem-solving process is a key factor for analyzing the prior difficulty of RC items, yet no scalable method currently exists for automatically measuring it. In this study, we investigated whether LLMs can predict the cognitive complexity of RC items through two cognitively grounded dimensions: Evidence Scope and Transformation Level. To this end, we constructed RECO—a benchmark dataset of RC items annotated along these two dimensions—and conducted a comprehensive evaluation of eight LLMs under diverse prompting and decoding configurations.

The results show that LLMs have strong potential as proxies for cognitive complexity estimation, with some open-source models—such as Qwen2.5-32B—achieving performance comparable to proprietary systems like GPT-4o. Nevertheless, LLMs are not fully aligned with human experts and exhibit limitations in their metacognitive abilities—particularly in detecting phrase reordering or identifying all necessary evidence from the passage. We hope our findings encourage further research in item difficulty estimation and difficulty-controlled item generation—contributing to the development of more interpretable and cognitively aligned educational NLP systems.

Limitations

Label Imbalance and Data Scale. Our dataset exhibits label imbalance across cognitive dimensions, which is an inevitable outcome of annotating RC items randomly sampled from assessments. The scarcity of certain labels can be attributed to several factors: such item types may be more difficult to create, less emphasized in instructional practice, or underrepresented in the specific assessments from which our samples were drawn. However, supplementing these underrepresented categories would require additional large-scale annotation, which was infeasible under our budget constraints.

Moreover, constructing the dataset required costly expert annotation—three raters per item—which constrained our ability to perform supervised fine-tuning. Nevertheless, our dataset comprises 776 items, a substantially larger resource than the previously released CMCQRD dataset containing only 289 items ([Mullooly et al., 2023](#)). Our findings also suggest that larger models (24B–32B) exhibit more robust in-context classification than smaller ones (7B–9B), thus highlighting opportunities for future work on data augmentation and knowledge distillation to build smaller yet effective models.

Limited Coverage of RC Item Types. The two cognitive dimensions investigated—Evidence Scope and Transformation Level—do not generalize across all RC item types in capturing their cognitive complexity. For instance, questions targeting main ideas or author intent inherently require multi-sentence inference. In contrast, the dimensions we employ are most relevant to factual detail questions such as TFNG, MTF, and WH-questions. Because different RC item types involve distinct cognitive complexity factors, addressing all of them comprehensively would be beyond the scope of a single study. In this work, we therefore focus on two key dimensions best captured by factual detail questions, as this question format spans a wide range of cognitive complexity—from single-sentence word matching to multi-sentence inference. Our goal is to establish a foundation for future research on additional factors across a broader set of RC item types.

Limits of a Single Factor in Explaining Item Difficulty. Finally, the two dimensions studied here represent only a subset of the many factors

influencing RC item difficulty. Establishing a direct or linear relationship between a single factor and difficulty would require controlling for all other variables, which is not the case in our dataset. For instance, a multi-sentence inference item may not necessarily be harder than a single-sentence paraphrasing item if the latter references a more complex passage. Thus, *these two factors alone cannot fully account for item difficulty*. This study instead focuses on testing whether LLMs can estimate cognitively grounded dimensions that have traditionally relied on human annotation.

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A Data Annotation Details

RACE++ (Lai et al., 2017; Liang et al., 2019) is a reading comprehension (RC) dataset consisting of English RC items sourced from exams administered to Chinese middle school, high school, and college students. To construct RECO, we use Multiple-choice True/False (MTF) items from the RACE++ dataset, each consisting of a reading passage and four options. We collected only items requiring holistic passage comprehension, excluding those targeting specific entities or local paragraph-level details. Items from the middle and high school levels were drawn from the test split, while college-level items were taken from the validation and test splits, due to limited data in its test set. Each MTF item was divided into four True/False/Not Given (TFNG) items, yielding triplets of (passage, statement, factuality label [*True* or *Not True*]).

We recruited three experts, who independently labeled 238 MTF items (952 statements) divided into six batches. Annotators were compensated per item according to the education level of the source test: \$1.20 for middle school, \$1.50 for high school, and \$2.00 for college-level items, with additional payment for training and revision.

Figure 8 illustrates examples of the annotation sheet used by annotators. For each statement, annotators were shown the passage, the statement, and its factuality label. Annotators first identified the sentence(s) necessary to verify the statement’s factuality (Evidence Scope) and then determined its Transformation Level based on the lexical and structural relationship between the statement and the selected evidence. Because TL is defined only for *True* statements, annotators revised each *False* statement—excluding those labeled as *Insufficient Evidence*—into its closest *True* version before assigning a TL label.

To further ensure data quality, we added two additional survey questions. First, annotators were asked whether they agreed with the provided factuality label, and items with disagreement were discarded. Second, they reported their confidence in the labels they assigned; although no low-confidence items were reported, any such cases would have been excluded. Finally, items flagged as potentially problematic or ethically inappropriate were also removed.

Figure 5 presents inter-annotator agreement for both annotation dimensions. Among the 898 items

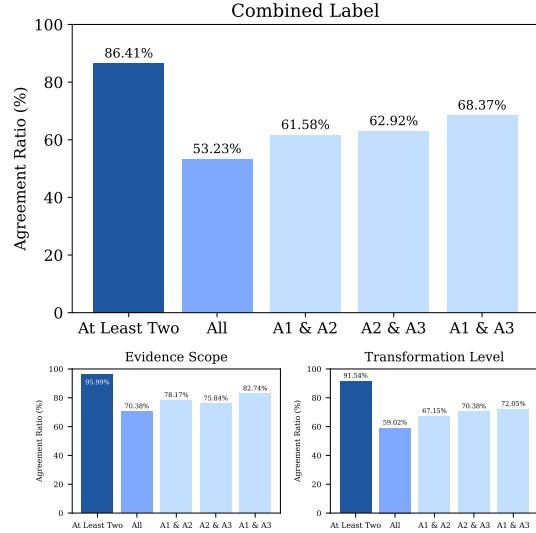


Figure 5: Inter-annotator agreement across labeling dimensions. Agreement ratios are shown for (top) combined labels of two dimensions. “At Least Two” indicates majority agreement among annotators, while “All” requires unanimous agreement. Pairwise agreements between annotators (A1, A2, A3) are also reported. For TL agreement, multi-evidence items labeled as *word matching* or *paraphrasing* were considered equivalent to *transformed word matching* and *transformed paraphrasing*, respectively.

retained after filtering based on annotators’ survey responses, 86.41% received the same label from at least two annotators, while 53.23% achieved full agreement among all three. Although the annotation process was guided by structured label definitions, it required close examination of lexical, syntactic, and inferential relationships between statements and evidence, making it more demanding than typical classification tasks. In some cases, minor oversights—such as missing subtle paraphrases or nuanced details—led to disagreements. To mitigate their impact on data quality, we removed items for which all three annotators provided different labels. For items with partial agreement (i.e., two matching labels and one dissenting), the authors manually reviewed all annotations and resolved discrepancies by cross-referencing annotators’ justifications with the passage content. After this adjudication process, we obtained 776 annotated TFNG items, which we refer to as RECO (Reading Comprehension dataset with Cognitive Complexity Annotations).

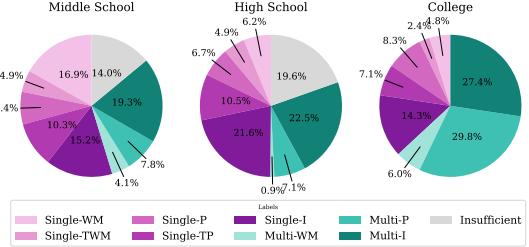


Figure 6: Distribution of combined difficulty labels in the RECO dataset across educational levels.

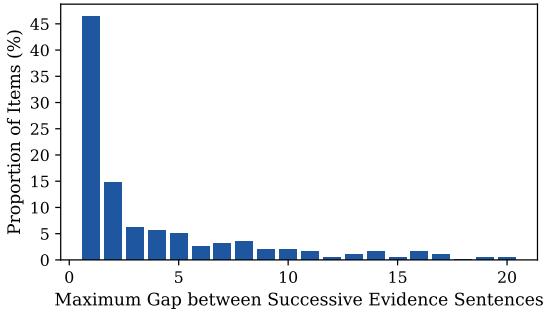


Figure 7: Distribution of the maximum gap between successive evidence sentences for multiple-sentence evidence items. For each item, the gap is measured as the largest distance between any two consecutive evidence sentences in the passage.

B Data Analysis

Figure 6 presents the distribution of cognitive labels in RECO across different educational levels. *Word-matching* items with *single-sentence evidence*—representing the lowest cognitive complexity—are more prevalent in middle school exams but decrease substantially at higher levels. Conversely, *multi-sentence* and *inference-based* items occur more frequently in high school and college assessments. These patterns suggest that cognitive complexity varies considerably even among items within the same educational level or format, implying that educational level alone is insufficient for fine-grained difficulty analysis.

Figure 7 illustrates the maximum gap between successive evidence sentences, as identified by the raters, for multi-sentence evidence items. According to the chart, approximately 45% of these items have evidence sentences that are adjacent in the passage, whereas about 55% require comprehension across sentences that are farther apart. This indicates that many items demand integration of information from non-contiguous parts of the passage, rather than relying solely on one or two consecutive sentences.

C Experimental Details

In our experiments, we used open-source models from Hugging Face⁴ with the following model names:

- Gemma2-9B: google/gemma-2-9b-bit
- Gemma2-27B: google/gemma-2-27b-bit
- Mistral-7B: mistralai/Mistral-7B-Instruct-v0.3
- Mistral-24B: mistralai/Mistral-Small-24B-Instruct
- Qwen2.5-7B: Qwen/Qwen2.5-7B-Instruct
- Qwen2.5-32B: Qwen/Qwen2.5-32B-Instruct

In addition, we used GPT-4o and GPT-4o-mini via the OpenAI API⁵, with model versions gpt-4o-2024-08-06 and gpt-4o-mini-2024-07-18, respectively.

For self-consistency decoding Wang et al. (2022), we used the default hyperparameter values of each model that the authors defined, especially for top- p , top- k , and temperature. All experiments were conducted using two NVIDIA A100 GPUs.

D Answer Reasoning vs. Metacognitive Awareness

We investigated whether LLMs with advanced reasoning capabilities are also effective at analyzing cognitive complexity. For this experiment, we used Qwen3-32B (Team, 2025), a reasoning-specialized model that supports a “thinking mode” designed for deep reasoning and self-reflection. We compared the performance of Qwen3-32B in two settings—with and without thinking mode—on the cognitive difficulty classification tasks. As a baseline, we also included Qwen2.5-32B, a model from the same family but not specialized for reasoning.

In Table 5, we observed that Qwen3-32B in thinking mode underperformed both its non-thinking-mode counterpart and Qwen2.5-32B, achieving lower F1 scores across both classification tasks. These results suggest that advanced reasoning and self-reflection capabilities do not necessarily enhance a model’s ability to classify cognitive complexity features such as ES and TL. This may be because these tasks do not require complex multi-step reasoning, but rather fine-grained categorization of human cognitive processes—something better handled through intuitive pattern recognition than abstract reasoning. The experimental results

⁴<https://huggingface.co>

⁵<https://openai.com>

Model	ES	TL (5-level)	TL (3-level)
Qwen2.5-32B	70.5	65.8	72.4
Qwen3-32B _{non-thinking}	67.9	66.3	78.9
Qwen3-32B _{thinking}	65.5	64.8	71.8

Table 5: Performance comparison of LLMs with and without deep-thinking capabilities.

align with this interpretation and highlight the distinction between problem-solving ability and the metacognitive awareness.

<p>1. Evidence Mapping</p> <p>Identify all sentences necessary to verify the factuality of the option. [Passage]</p> <hr/> <p><input type="checkbox"/> On a small farm in Mexico, there are no schools. <input type="checkbox"/> A bus is the school! <input type="checkbox"/> The driver of the bus is the teacher! <input type="checkbox"/> It is a school bus, but it doesn't take children to school. <input type="checkbox"/> It just goes round from place to place, and sometimes it comes to this farm. <input type="checkbox"/> The bus will stay here for three months. <input type="checkbox"/> The farmers call it a school on wheels. <input type="checkbox"/> Every time the bus comes, the farmers come running to it, shouting and laughing. <input type="checkbox"/> They warmly welcome the school bus! <input type="checkbox"/> When the bus is on the farm, in the morning, the teacher teaches the small children. <input type="checkbox"/> In the afternoon, the bigger children come to have their lessons because they must work in the morning. <input type="checkbox"/> At night, the fathers and mothers come to school. <input type="checkbox"/> They want to learn, too. <input type="checkbox"/> How the farmers hope that some day they can have a real school on their farm!</p> <hr/> <p>Option A. The children and their parents on the farm all come to the bus school to learn. (True)</p> <p>2. Reasoning Complexity Measurement</p> <p>Identify the level of reasoning required to determine the factuality of the option.</p> <p>(i) When a single sentence alone is sufficient to determine the factuality of the option,</p> <p><input type="radio"/> Word Matching <input type="radio"/> Transformed Word Matching <input type="radio"/> Paraphrase <input type="radio"/> Transformed Paraphrase <input type="radio"/> Inference</p> <p>(ii) When multiple sentences from the passage are required together to determine the factuality of the option,</p> <p><input type="radio"/> Word Matching <input type="radio"/> Paraphrase <input type="radio"/> Inference</p> <p>3. Additional Survey</p> <p>Do you agree that this option is True?</p> <p><input type="radio"/> Yes <input type="radio"/> No</p> <p>I am confident that my response is correct.</p> <p><input type="radio"/> Strongly agree <input type="radio"/> Somewhat agree <input type="radio"/> Somewhat disagree <input type="radio"/> disagree</p>	<p>1. Evidence Mapping</p> <p>Identify all sentences necessary to verify the factuality of the option. [Passage]</p> <hr/> <p><input type="checkbox"/> On a small farm in Mexico, there are no schools. <input type="checkbox"/> A bus is the school! <input type="checkbox"/> The driver of the bus is the teacher! <input type="checkbox"/> It is a school bus, but it doesn't take children to school. <input type="checkbox"/> It just goes round from place to place, and sometimes it comes to this farm. <input type="checkbox"/> The bus will stay here for three months. <input type="checkbox"/> The farmers call it a school on wheels. <input type="checkbox"/> Every time the bus comes, the farmers come running to it, shouting and laughing. <input type="checkbox"/> They warmly welcome the school bus! <input type="checkbox"/> When the bus is on the farm, in the morning, the teacher teaches the small children. <input type="checkbox"/> In the afternoon, the bigger children come to have their lessons because they must work in the morning. <input type="checkbox"/> At night, the fathers and mothers come to school. <input type="checkbox"/> They want to learn, too. <input type="checkbox"/> How the farmers hope that some day they can have a real school on their farm!</p> <hr/> <p>Option B. A school bus is a real school for farmers' children. (Not True)</p> <p>2. Reasoning Complexity Measurement (NO EVIDENCE selected: skip this section.)</p> <p>Identify the level of reasoning required to determine the factuality of the option.</p> <p>Revise only the portion of the option that conflicts with the passage. Apply minimal edits, and make use of wording from the evidence sentence whenever possible.</p> <hr/> <p>Assess the reasoning complexity based on your revised option.</p> <p>(i) When a single sentence alone is sufficient to determine the factuality of the option,</p> <p><input type="radio"/> Word Matching <input type="radio"/> Transformed Word Matching <input type="radio"/> Paraphrase <input type="radio"/> Transformed Paraphrase <input type="radio"/> Inference</p> <p>(ii) When multiple sentences from the passage are required together to determine the factuality of the option,</p> <p><input type="radio"/> Word Matching <input type="radio"/> Paraphrase <input type="radio"/> Inference</p> <p>3. Additional Survey</p> <p>Do you agree that this option is Not True?</p> <p><input type="radio"/> Yes <input type="radio"/> No</p> <p>I am confident that my response is correct.</p> <p><input type="radio"/> Strongly agree <input type="radio"/> Somewhat agree <input type="radio"/> Somewhat disagree <input type="radio"/> disagree</p>
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Figure 8: Example annotation sheets for *True* (left) and *Not True* (right) statements. For *Not True* statements, annotators could mark “No Evidence” when the passage lacked sufficient information (corresponding to the *Insufficient Evidence* category). Annotators were also asked to create a minimally revised *True* version of each *False* statement to enable assessment of its Transformation Level.