FEANEL: A Benchmark for Fine-Grained Error Analysis in K-12 English Writing

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Abstract

Large Language Models (LLMs) have transformed artificial intelligence, offering profound opportunities for educational applications. However, their ability to provide fine-grained educational feedback for K-12 English writing remains underexplored. In this paper, we challenge the error analysis and pedagogical skills of LLMs by introducing the problem of Fine-grained Error Analysis for English Learners and present the *Fine-grained Error ANalysis for English Learners* (**FEANEL**) Benchmark. The benchmark comprises 1,000 essays written by elementary and secondary school students, and a well-developed English writing error taxonomy. Each error is annotated by language education experts and categorized by type, severity, and explanatory feedback, using a part-of-speech-based taxonomy they co-developed. We evaluate state-of-the-art LLMs on the FEANEL Benchmark to explore their error analysis and pedagogical abilities. Experimental results reveal significant gaps in current LLMs' ability to perform fine-grained error analysis, highlighting the need for advancements in particular methods for educational applications.

1 Introduction

Large Language Models (LLMs) have revolutionized artificial intelligence with their extensive knowledge and remarkable reasoning capabilities (He et al., 2025), creating unprecedented opportunities in educational applications (Wang et al., 2024c; Yan et al., 2024a; Chu et al., 2025c; Xu et al., 2024). In language education, LLM-powered solutions are increasingly being deployed to enhance personalized learning experiences (Ye et al., 2025b; Liu et al., 2025). However, while LLMs demonstrate impressive performance in many tasks, their application in providing fine-grained educational feedback targeted at each error humans may make (Wang et al., 2024b; Stahl et al., 2024; Yan et al., 2024b; Han et al., 2023), which is critical for language acquisition, remains under-explored.

Current related methodologies, however, typically focus on surface-level corrections (Bryant et al., 2023; Huang et al., 2023; Ye et al., 2023b) or global assessments with coarse feedback (Do et al., 2024; Ke and Ng, 2019), which do not capture the multifaceted nature of writing difficulties. Moreover, the lack of a standardized taxonomy for English writing errors (Zou et al., 2025) has led to inconsistencies in error categorization and hindered the development of robust educational tools. These gaps are particularly pronounced in K-12 English education, where learners exhibit diverse proficiency levels and error patterns that require fine-grained analysis and personalized feedback.

Therefore, this paper define the problem of *Fine-grained Error Analysis for Language Learners*, a crucial component of language education aimed at systematically analyzing learners' errors in written English. Error analysis, as a foundational methodology in second language acquisition research (James, 2013; Erdoğan, 2005), serves two primary purposes: (1) investigating the underlying causes of errors to facilitate targeted interventions, and (2) providing insights into common difficulties in language learning to inform teaching practices and materials. By offering detailed feedback on error types, severity, and corrections, this problem not only supports learners in scaffolding their knowledge but also enhances their ability to learn from mistakes through instant and interpretable feedback (Daheim et al., 2024; Ye et al., 2025a).

To investigate this problem, we introduce the *Fine-grained Error ANalysis for English Learners* (**FEANEL**) Benchmark, designed to advance research in fine-grained error analysis. The benchmark includes a dataset of 1,000 essays written by K-12 students, with 500 essays (3,003 errors) from elementary school students and 500 essays (5,671 errors) from secondary school students, cov-

ering a wide range of age groups and proficiency levels. Each error analysis has been meticulously annotated with an error type, severity level, and explanation, guided by a taxonomy co-developed with language education experts.

As illustrated in Figure 1, this paper goes beyond conventional automated essay scoring (Ke and Ng, 2019) and grammatical error correction (Bryant et al., 2023; Zeng et al., 2024) by highlighting the interpretability and educational value of feedback, thereby facilitating a more thorough evaluation of LLMs within language education. Moreover, the benchmark establishes a rigorous framework for evaluating fundamental competencies of LLMs, including their comprehension of syntactic, grammatical, and lexical knowledge and their capacity to replicate pedagogical scenarios by producing engaging and didactically significant feedback. Additionally, FEANEL also evaluates LLMs' capacity for commonsense reasoning and knowledge application, recognizing that effective error analysis in essays often involves understanding logical relationships and world knowledge (e.g., an essay requiring an introduction of tourist attractions in Beijing). This multidimensional evaluation provides a more detailed understanding of LLMs' efficacy in providing insightful and contextually relevant feedback to learners.

We conduct extensive experiments to evaluate the performance of various LLMs on FEANEL. Our empirical study reveals: (1) LLMs still face significant challenges in classifying complex errors, and often fall short of human-level pedagogical nuance in their explanations. (2) Performance of LLMs is highly dependent on the detail level of prompts and the availability of examples. (3) LLMs are sensitive to the sub-task execution order. We believe that our proposed FEANEL and findings are crucial for educational applications and understanding LLMs' pedagogical ability. In summary, our contributions are threefold:

- We define the problem of Fine-grained Error Analysis and introduce the FEANEL Benchmark, a novel dataset annotated by English education experts for fine-grained error analysis in writing.
- We develop a well-defined and part-of-speech-driven taxonomy for English writing errors, addressing the issues of inconsistent categorization and insufficient granularity in previous work.
- We conduct a comprehensive empirical evaluation of various LLMs, providing insights into their capabilities and limitations in generating interpretable and pedagogically valuable feedback.

2 The FEANEL Benchmark

2.1 Problem Definition

Given an essay prompt P, a student's written answer X, its corrected version Y, and a set of edits $\mathbb{E} = \{e_1, e_2, \cdots, e_N\}$ that transform X to Y[1], the problem of fine-grained error analysis focuses on analyzing each specific edit/error. Each analysis comprises three key elements: (1) **Error Classification**: Categorize the error into an error type $t_i \in \mathcal{T}$ based on the pre-defined taxonomy $\mathcal{T}$. (2) **Error Severity Rating**: Assign a numerical score $s_i \in \{1, 2, 3, 4, 5\}$ to indicate how critically each error affects the sentence's overall structure and meaning. (3) **Error Explanation**: Provide an accurate, relevant, and sufficient explanation d_i of why it is an error and how to correct or prevent it. Notice that there may be multiple errors in an edit. We require LLMs to assign a single error type with the highest priority, while also explaining all error types in the explanation. By default, LLMs are required to generate an error analysis in the order of Error Severity → Error Type → Error Explanation, which is formulated as:

$$\begin{aligned} P(s_i, t_i, d_i \mid X, Y, e_i) = P(s_i \mid X, Y, e_i) \cdot \\ P(t_i \mid X, Y, e_i, s_i) \cdot P(d_i \mid X, Y, e_i, s_i, t_i) \end{aligned} \tag{1}$$

2.2 Dataset Construction

Data Collection. We collected original essays from two distinct sources to ensure diversity in learner proficiency and educational context, which offers a rich spectrum of fine-grained error analysis for varying writing capabilities. First, essays from elementary school students aged 9-11 were collected through a global online education platform, where students are primarily non-native speakers from around the world. Other essays were sourced from the TECCL Corpus[2], a significant corpus of Chinese EFL learners' writing. It is notable for its wide array of over 1,000 essay topics and its representation of learners from elementary to postgraduate levels. For our study, we selected essays corresponding to middle school proficiency (corresponding to students aged 12-18). These essays

[1] In this paper, each edit $e_i \in \mathbb{E}$ is considered an instance of an error, as edits are introduced only to rectify mistakes.

[2] https://corpus.bfsu.edu.cn/info/1070/1449.htm

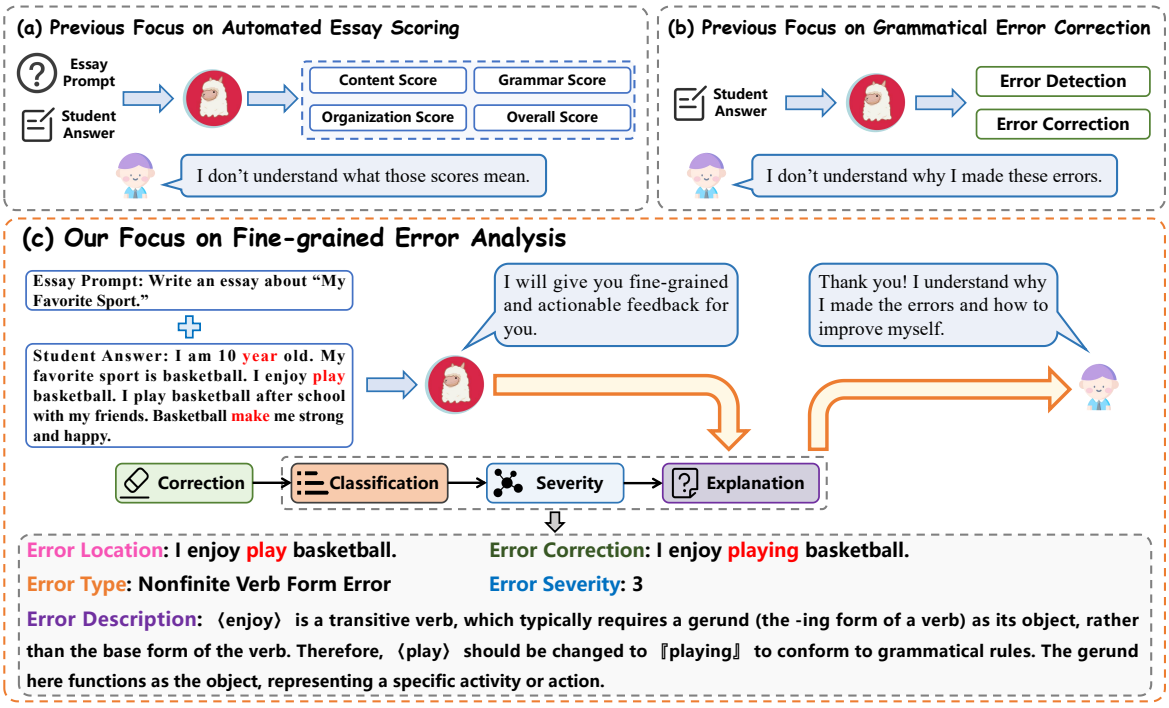

Figure 1: Comparison of our focus on Fine-grained Error Analysis with existing studies.

primarily cover topics such as family, study, friendship, and life. All data from both sources was fully anonymized before use to ensure compliance with privacy regulations. We remove the essays concerning personal privacy.

Data Cleaning. To ensure the quality and relevance of the data for our analysis, a rigorous cleaning process was implemented by a team of annotators. Essays were excluded if they: (1) significantly deviated from the given prompt, rendering them off-topic; (2) contained an insufficient number of words, indicating a lack of substantive response; (3) were entirely error-free, as our focus is on error analysis; or (4) were incomplete or nonsensical. Following this filtering, the original formatting of the retained essays was preserved to maintain the authenticity of student responses with real errors. Finally, 500 elementary and 500 secondary essays are selected to construct the dataset.

Data Annotation. The data underwent annotation by English education experts with over five years of teaching experience. The comprehensive annotation workflow was as follows:

(1) **Error Detection and Correction**: Following established Grammatical Error Correction (GEC) guidelines (Bryant et al., 2023), education experts rewrote student essays, applying the *minimal* necessary corrections to preserve the original meaning of the essays. This principle ensures objectivity and facilitates accurate error categorization. Experts subsequently reviewed these corrections, checking for over-corrections, missed corrections, or incorrect revisions to guarantee accuracy and consistency. We then leverage the edit extraction tool *CLEME* (Ye et al., 2023b, 2024) to extract a set of edits describing the revision trajectory from X to Y for subsequent annotation of error analysis.

(2) **Error Type Taxonomy**: In collaboration with two experienced educators, we developed an error type taxonomy comprising 29 distinct error types, primarily based on part-of-speech categories (see Appendix A.1). The taxonomy was designed separately from the dataset for generalization, highlighting *broad coverage* and *mutual exclusivity* with appropriate granularity. It enables precise classification of nearly all errors without resorting to a vague "Other Error" category. Before formal annotation, the taxonomy underwent evaluation and enhancement utilizing a subset of the dataset. A prioritization system is detailed in Appendix A.1, designed to ascertain the most significant error type in cases of complex errors that involve multiple error types.

(3) **Error Analysis**: Each identified error underwent a three-step analysis: (1) *Error Classification*:

	Essays	Essay Len.	Edits/Essay	Edit Len.	Exp. Len.
Ele.	500	48.2	6.01	1.66	69.27
Sec.	500	127.1	11.34	1.53	52.79

Table 1: Dataset statistics of the FEANEL benchmark. We list the average length and edit number per essay. Length (Len.) is presented as word count.

Experts assigned the most prioritized error type to each edit. (2) *Error Severity Rating*: A 1-5 scale was used to determine the seriousness of each error's impact on sentence structure and meaning. We define and exemplify each severity level in Appendix A.2. (3) *Error Explanation*: At least two experts independently provided detailed explanations for each error, adhering to principles of accuracy, relevance, and sufficiency. Another expert then reviewed and selected the most appropriate explanation, refining it for clarity and completeness if necessary.

2.3 Dataset Analysis

Dataset Statistics. The overall statistics of the FEANEL benchmark are presented in Table 1. The dataset comprises 1,000 essays, evenly split with 500 from elementary school students and 500 from secondary school students. Secondary school essays are considerably longer. This difference in length correlates with the number of identified edits: elementary school essays contain 3,005 edits, while secondary school essays feature significantly more, 5,671 edits. In total, the benchmark includes 8,676 fine-grained error analyses. We provide further analysis of error type distribution on both domains in Appendix A.3.

2.4 Evaluation Metrics

We evaluate the fine-grained error analysis task along its three core components. For Error Classification, we report Accuracy to capture overall correctness and Macro-F1 to ensure balanced assessment across all categories, particularly highlighting performance on long-tail distributions. Error Severity Rating is assessed using Mean Absolute Error (MAE). To evaluate Error Explanation quality, we employ standard n-gram-based metrics, i.e., BLEU (Papineni et al., 2002), METEOR (Banerjee and Lavie, 2005), and ROUGE-L (Lin, 2004). This combined set of metrics provides a robust and complementary evaluation protocol.

3 Experiments

3.1 Experimental Settings

Baseline Models. We evaluate the performance of various LLMs on our FEANEL benchmark to investigate their ability to perform error analysis. The experiment involve state-of-the-art reasoning models as well as other representative models, including GPT-4o (Hurst et al., 2024), o1 (Jaech et al., 2024), o3 (OpenAI, 2025), o4-mini (OpenAI, 2025), Gemini-2.5-pro (Team et al., 2023), DeepSeek-R1 (Guo et al., 2025), Claude-3.7-Sonnet (claude, 2025), Claude-3.7-Sonnet-Thinking (claude, 2025), Grok-3-Beta (grok, 2025), Qwen-3 (Team, 2025), Llama-3 (Grattafiori et al., 2024), and Mistral-Small-3.1 (AI, 2025). These models represent a mix of closed-source commercial systems and open-source models, ensuring a comprehensive evaluation across different architectures and training paradigms. We report evaluation details and design prompts in Appendix B.

Evaluation Settings. We design three distinct experimental settings to evaluate the LLMs' performance on the FEANEL benchmark under varying levels of instructional detail. This comprehensive approach allows us to systematically assess the LLMs' intrinsic understanding of the task versus their ability to leverage explicit guidance, providing insights into their robustness and adaptability. (1) **`Zero-shot-naive`**: LLMs are provided with only the basic task instruction and the label space for our error taxonomy. Crucially, they do not receive any demonstrations, detailed definitions, or illustrative examples for each error type, nor are they given definitions for the severity scores (1-5). The purpose of this setting is to test the LLMs' unassisted ability to perform fine-grained error analysis with minimal contextual information, thereby establishing a baseline for their inherent capabilities. (2) **`One-shot-detailed`**: The setting builds directly upon the `Zero-shot-naive` setting by offering more comprehensive guidance and demonstrations. Models receive a detailed definition and example for every error type within our taxonomy, along with an explicit definition for each severity score from 1 to 5. The given demonstration allows us to investigate the LLMs' capacity for in-context learning and their ability to generalize effectively from a specific, relevant example.

The progression from `Zero-shot-naive` to `One-shot-detailed` systematically increases the

Model	Think	Classification				Severity		Explanation					
		Acc↑		F_1↑		MAE↓		BLEU↑		METEOR↑		ROUGE↑	
GPT-4o	✗	61.74	66.79	46.55	52.67	0.87	0.77	1.35	1.19	17.87	17.58	24.29	23.02
o1	✓	68.60	74.27	**62.64**	64.50	0.68	0.60	0.82	1.00	15.37	16.12	23.95	23.04
o3-low	✓	70.93	74.79	62.47	**66.06**	0.69	0.63	1.32	1.16	17.62	17.10	24.12	22.95
o4-mini-low	✓	69.80	71.43	55.28	60.97	0.82	0.80	1.44	1.18	17.73	16.44	26.06	23.40
o4-mini-medium	✓	68.83	70.87	54.63	58.86	0.79	0.80	1.48	1.29	18.07	16.85	26.43	23.78
o4-mini-high	✓	69.56	72.89	55.72	61.33	0.79	0.46	1.51	1.34	18.03	17.50	26.14	24.51
Gemini-2.5	✓	**72.06**	**76.34**	60.67	65.95	0.80	0.79	**3.15**	**2.61**	**25.36**	**24.21**	**28.61**	26.15
DeepSeek-R1	✓	67.87	72.51	54.79	60.41	0.76	0.72	1.57	1.37	17.25	16.83	28.31	**26.29**
Claude-3.7	✗	64.57	70.04	51.56	58.60	0.76	0.68	2.50	2.20	22.17	22.81	26.42	24.90
Claude-3.7	✓	71.40	74.65	58.59	60.56	0.69	0.65	2.17	2.00	21.12	21.41	26.82	25.13
Grok-3	✗	66.90	72.69	52.92	59.14	**0.67**	**0.59**	2.37	1.70	24.67	24.07	26.06	23.55
Mistral-small	✗	57.48	66.03	44.34	50.92	0.75	0.65	1.84	1.56	20.37	20.62	25.58	23.87
Qwen-3-8b	✓	57.44	61.28	41.04	45.38	0.90	0.79	0.97	0.67	15.62	14.74	23.51	21.45
Qwen-3-30b-a3b	✓	61.57	65.19	44.42	49.83	0.76	0.70	0.92	0.81	15.39	15.59	24.49	22.16
Qwen-3-230b-a22b	✓	62.50	68.66	49.84	55.64	0.84	0.82	0.82	0.82	14.42	14.31	22.64	21.23
Llama-3.1-8b	✗	35.33	40.25	23.17	26.07	1.13	1.10	0.64	0.54	15.97	15.54	21.47	19.61
Llama-3.1-70b	✗	53.28	59.12	42.46	45.04	0.79	0.73	1.24	0.83	17.37	16.38	23.42	21.25
Llama-3.3-70b	✗	56.48	63.12	41.84	46.69	0.95	0.92	1.52	1.17	19.28	19.46	21.48	20.26
Average	-	63.13	67.83	50.16	54.92	0.80	0.73	1.54	1.30	18.54	18.2	24.99	23.14
Human	-	79.90	76.66	60.53	62.25	0.99	0.72	5.21	5.20	25.28	28.39	33.50	31.60

Table 2: Main results of the `Zero-shot-naive` setting. We color the secondary results. The result of the *Human* block is collected from English teachers not involved in the dataset construction (Section 3.3). It is not fully comparable to the results of LLMs since human evaluation is conducted on a subset of the full dataset.

richness and explicitness of the input prompt. This design gradually reduces the task's inherent ambiguity and difficulty for the models.

3.2 Evaluation Results

The comprehensive results of our experiments across the three evaluation settings are presented in Table 2 for `Zero-shot-naive` and Table 3 for `One-shot-detailed`. Our analysis across these settings reveals several key insights into the capabilities and limitations of current LLMs.

Overview results. The overall results reveal that no LLM consistently outperforms others across all three sub-tasks. (1) For *Error Classification*, larger models often designated as thinking models, including Gemini-2.5-pro, o3-low, o1, o4-mini, Claude-3.7-Thinking, and DeepSeek-R1, generally demonstrate superior accuracy. This may be attributed to their enhanced reasoning capabilities, which are beneficial for systematically applying our taxonomy to complex linguistic errors. (2) In the *Error Severity Rating* task under the `Zero-shot-naive` setting, models such as Grok-3, o1, o3-low, and Claude-3.7-Thinking showed stronger performance, potentially reflecting better intuitive calibration for impact assessment. However, with the provision of detailed definitions and an example in the `One-shot-detailed` setting, models like Claude-3.7, Llama-3.3-70b, and Claude-3.7-Thinking excelled. (3) For the *Error Explanation* task, all LLMs show low BLEU, METEOR, and ROUGE scores compared to other NLP generation tasks such as machine translation, indicating the difficulty and subjectivity of the task. Specifically, Gemini-2.5-pro exhibited a significant lead, followed by models like Claude-3.7, o1, o3-low, and o4-mini. This highlights that models with strong generative capabilities are better suited for producing high-quality and pedagogically relevant textual feedback.

For the error classification task. We observe that classifying errors in essays from elementary school students is generally more challenging than for those from secondary school students. Across various models, the accuracy (Acc) for elementary-level essays is typically 2∼6 percentage points lower than for secondary-level essays. We hypothesize this is primarily because elementary students are more prone to making compound errors, where

Model	Think	Classification				Severity		Explanation					
		Acc↑		F_1↑		MAE↓		BLEU↑		METEOR↑		ROUGE↑	
GPT-4o	✗	66.57	72.02	52.97	57.66	0.78	0.66	2.46	2.16	19.96	19.70	28.41	26.13
o1	✓	74.49	77.80	63.94	65.57	0.82	0.69	2.27	2.61	19.04	20.49	29.42	**29.11**
o3-low	✓	**76.26**	**78.45**	**65.95**	65.20	0.77	0.69	2.30	2.01	19.96	19.04	27.79	25.61
o4-mini-low	✓	73.43	75.10	62.98	62.36	0.86	0.81	2.43	2.35	19.86	19.54	28.91	27.07
o4-mini-medium	✓	73.19	75.24	60.57	62.80	0.86	0.79	2.63	2.32	20.47	19.66	29.43	27.03
o4-mini-high	✓	73.53	74.79	64.71	62.04	0.86	0.80	2.58	2.28	20.22	19.77	28.99	27.28
Gemini-2.5	✓	76.19	77.17	65.60	64.79	0.75	0.74	**4.29**	**3.57**	**26.76**	**25.42**	**31.36**	28.06
DeepSeek-R1	✓	71.23	75.53	60.65	**66.38**	0.90	0.75	1.90	1.71	17.71	17.27	28.14	25.42
Claude-3.7	✗	69.50	75.73	55.38	62.69	**0.71**	**0.63**	3.61	3.24	22.67	22.85	29.71	27.74
Claude-3.7	✓	73.99	77.02	59.98	63.32	0.74	0.68	3.61	3.21	22.60	22.66	29.73	27.22
Grok-3	✗	67.10	74.09	52.99	60.29	0.97	0.88	3.63	2.76	24.17	23.43	29.60	26.86
Mistral-small	✗	63.64	68.68	49.69	52.93	0.94	0.81	3.06	3.33	22.14	23.53	30.50	29.26
Qwen-230b-a22b	✓	67.40	71.75	55.33	59.30	0.85	0.73	1.85	1.64	17.68	17.62	26.26	24.45
Qwen-30b-a3b	✓	63.47	68.71	47.22	54.33	1.05	0.84	1.33	1.34	16.69	17.25	26.05	24.57
Qwen-8b	✓	57.81	62.65	41.26	47.45	0.98	0.82	1.69	1.48	17.62	17.56	26.46	24.24
Llama-3.1-8b	✗	37.43	41.49	24.61	27.27	1.02	0.98	1.24	1.14	17.91	17.56	24.56	24.36
Llama-3.1-70b	✗	59.51	64.30	46.10	49.95	0.81	0.72	1.55	1.41	17.04	16.27	25.72	23.38
Llama-3.3-70b	✗	61.17	65.53	47.26	49.63	0.73	0.67	2.16	2.30	19.27	20.30	26.38	24.66
Average	-	66.85	70.61	54.22	57.13	0.86	0.77	2.41	2.21	19.95	19.83	28.10	26.16
Human	-	79.90	76.66	60.53	62.25	0.99	0.72	5.21	5.20	25.28	28.39	33.50	31.60

Table 3: Main results of the `One-shot-detailed` setting. We color the secondary results. The result of the *Human* block is collected from English teachers not involved in the dataset construction (Section 3.3). It is not fully comparable to the results of LLMs since human evaluation is conducted on a subset of the full dataset.

a single edit may involve multiple intertwined linguistic issues, often spanning more words (Table 1). This inherent complexity in the error instances naturally increases the difficulty of assigning a single salient error category. Furthermore, the Macro F1 scores for error classification are consistently and significantly lower than accuracy scores across all models and settings. This discrepancy indicates that while models may perform reasonably well on frequent error types, their ability to accurately classify less frequent error types remains limited. A detailed analysis of model performance on each specific error type is presented in Appendix C.

For the connection between different sub-tasks. A notable trend emerging from our results is that models exhibiting superior performance in the Error Classification task also tend to generate higher-quality explanations. It suggests an intrinsic link between the ability to categorize an error and the ability to articulate a meaningful and pedagogically sound explanation for it. This finding highlights the importance of understanding accurate errors as a foundational prerequisite for effective feedback. To further investigate this phenomenon and the potential benefits of optimizing this interplay, we conduct an ablation study, presented in Appendix C.2, to explore the impact of varying execution order.

For the impact of the information richness of the prompt. Our experiments demonstrate a clear positive correlation between the richness of information provided in the prompt and the models' performance in both error classification and explanation. Specifically, transitioning from `Zero-shot-naive` to `One-shot-detailed` leads to a marked improvement in average classification Accuracy, Macro F1 scores, and all explanation metrics. It reveals that the problem of fine-grained error analysis can derive substantial benefit from clear definitions and concrete examples. This highlights the differential impact of effective prompt engineering strategies on performance.

For the impact of Thinking Models. Comparing the performance of models with explicit "thinking" or chain-of-thought-like mechanisms, such as Claude-3.7-Sonnet-Thinking, against their base counterparts (e.g., Claude-3.7-Sonnet), reveals interesting patterns. The Thinking variant consistently achieves significantly higher Accuracy and

Macro F1 scores across the different settings in the error classification task. However, their performance on error severity rating and explanation quality remains comparable to the non-thinking versions. This suggests that while structured reasoning processes can enhance the ability to dissect and categorize errors accurately, they may not confer a similar advantage for tasks perceived as more intuitive or requiring nuanced pedagogical capability. This distinction helps isolate the specific benefits of such reasoning mechanisms and points to areas where other approaches might be needed.

For the model performance of different scale parameters. In line with general expectations from scaling laws, we observe that larger models typically yield better performance across the tasks in the FEANEL benchmark. For instance, within the Qwen3 series, there is a general trend of improvement as model size increases from Qwen-3-8B to Qwen-3-30B-A3B, and further to Qwen-3-230B-A22B, across all three evaluation settings. This indicates that increased capacity often leads to better generalization and task execution. However, there are exceptions to this trend. For example, Qwen-3-30B-A3B occasionally exhibits slightly superior performance on certain explanation quality metrics compared to the larger Qwen-3-230B-A22B. We attribute this to the specific pre-training and fine-tuning objectives of the Qwen-3 series, which have a strong emphasis on mathematical and coding reasoning tasks. This enhanced reasoning capability, while beneficial for many applications, may not directly or fully translate to the nuanced pedagogical communication and descriptive abilities required by our benchmark. Therefore, advancing model alignment for educational tasks and enhancing their capacity for precise, pedagogically sound error description remain significant research challenges.

3.3 Human Evaluation Results.

To gauge the performance gap between LLMs and human intelligence, we engaged several English teachers to conduct fine-grained error analysis on a randomly selected subset of 500 errors from elementary school essays and an additional 500 from secondary school essays. These teachers were not involved in the dataset construction and received no specialized training. This design choice allows us to benchmark LLM performance against the capabilities of human teachers operating without extensive task-specific instruction.

For both error classification and explanation, human teachers almost outperform all evaluated LLMs, particularly under the Zero-shot-naive setting. This underscores a considerable gap between current AI capabilities and human-level expertise in the nuanced task of fine-grained error analysis. The results validate that our benchmark effectively identifies areas where LLMs have substantial room for improvement, thereby justifying its utility in driving research. While enriching prompts with detailed instructions and in-context examples does improve LLM performance and narrow this gap, LLMs still often require more extensive contextual information than humans. Moreover, their generated explanations, even when technically correct, can sometimes lack the conciseness, pedagogical appropriateness, or adaptive nuance of human-authored feedback.

3.4 Case Study

We present a case study analyzing a complex error from representative LLMs. We notice that GPT-4o misclassifies the error type for the entire edit as "Verb Choice Error." While its explanation correctly identifies the subject-verb agreement violation for "is" $\rightarrow$ "are", this is not reflected in the main error type assigned. Secondly, in its explanation for the second error component ("check" $\rightarrow$ "cheap"), GPT-4o mistakenly refers to the incorrect word "check" as an "adjective". On the other hand, the semantic content of o3-mini's explanation is reasonable, but the output does not fully adhere to the desired structured formatting conventions exemplified in the ground truth. For instance, it omits the explicit labeling of each error component within the explanation. Adherence to such formatting is not merely stylistic; it is crucial for consistent automated parsing of results and for providing clear, standardized feedback to learners. Gemini-2.5-pro classifies the "check" $\rightarrow$ "cheap" error as a PoS Confusion Error, which is wrong since they do not have the same root or affix.

This typical case study highlights several recurring challenges for LLMs in our experiments: accurately determining the single most salient and correct error type when multiple errors are present in an edit, consistently applying specific error taxonomies, and adhering strictly to specified output formatting. It underscores that the intricate reasoning and didactic skills essential for granular educational feedback are still developing in LLMs.

Example

Error Sentence: Mr. Cool Clothes Store's clothes is very check now.
Correct Sentence: Mr. Cool Clothes Store's clothes are very cheap now.

Ground Truth: Error Type: Subject-Verb Agreement Error, Error Severity: 4
Error Explanation: ① Subject-Verb Agreement Error: The subject ⟨clothes⟩ is plural and requires the plural verb [are], so ⟨is⟩ is changed to [are] to conform to grammatical rules; ② Adjective Error: ⟨check⟩ means to examine; the adjective [cheap] indicating price should be used here, so ⟨check⟩ is changed to [cheap] to convey the correct meaning.

GPT-4o: Error Type: Verb Choice Error, Error Severity: 4
Error Explanation: ① The verb ⟨is⟩ is incorrectly used for the plural subject ⟨clothes⟩, violating subject-verb agreement rules. The correction [are] ensures proper agreement. ② The adjective ⟨check⟩ is semantically inappropriate in this context, as it does not convey the intended meaning of being inexpensive. The correction [cheap] provides the proper adjective to convey the intended meaning.

o3-low: Error Type: Subject-Verb Agreement Error, Error Severity: 3
Error Explanation: ⟨is⟩ violates the rule that the plural subject "clothes" requires a plural verb; [are] restores subject-verb agreement. ②The word ⟨check⟩ is a misspelling/wrong form of the adjective "cheap"; replacing it with [cheap] provides the correct meaning.

Gemini-2.5-pro: Error Type: PoS Confusion Error, Error Severity: 4
Error Explanation: ① Subject-Verb Agreement Error: The subject of the sentence is "clothes," which is a plural noun. The verb used, ⟨is⟩, is singular. The verb must agree in number with its subject, so the plural verb [are] is required; ② PoS Confusion Error: The word ⟨check⟩ is used incorrectly here. The context requires an adjective following "very" to describe the clothes. ⟨check⟩ is typically a verb or a noun. The correct adjective meaning "low in price" is [cheap].

Figure 2: A case of error analysis.

4 Related Work

LLMs for Education. Recent advances in LLMs have spurred a wide range of educational applications, including answer grading (Schneider et al., 2023; Chu et al., 2025b), educational question generation (Li and Zhang, 2024; Biancini et al., 2024), interactive educational chatbots (Dan et al., 2023; Lieb and Goel, 2024; Wang et al., 2024a), and classroom simulation (Zhang et al., 2025b; Gao et al., 2025; Yue et al., 2024). These systems leverage deep generative capabilities to provide personalized feedback (Borges et al., 2024; Nair et al., 2024; Zhang et al., 2025a) and scaffold learners' understanding (Liu et al., 2024; Scarlatos et al., 2025). For instance, LLM-based tutoring systems have shown promise in delivering real-time corrections and explanations for complex tasks (Treviso et al., 2024; Kim et al., 2024). However, ensuring that LLM-based feedback is accurate, bias-free, and pedagogically grounded remains an open challenge (Ye et al., 2025b; Chu et al., 2025c). Our work fills the gap in the lack of error analysis in the context of language education.

LLMs for Language Learning. A growing body of work has specifically examined how LLMs can support second-language (L2) learners. Early efforts in automated essay scoring leveraged feature engineering or neural networks to produce holistic ratings (Taghipour and Ng, 2016; Ke and Ng, 2019), while more recent studies exploit instruction-tuned LLMs to generate both scores and rubric-based rationales (Chu et al., 2025a; Do et al., 2025). In grammatical error correction (Ye et al., 2023a), LLM prompting has been shown to narrow the gap between supervised systems and human annotators (Li and Wang, 2024; Kong et al., 2025). Despite encouraging results, evaluations reveal that LLM-generated feedback may be overly generic or introduce hallucinated corrections (Han et al., 2024; Rüdian et al., 2025), underscoring the need for fine-grained and pedagogically sound analysis—a gap our benchmark explicitly targets.

5 Conclusion

This paper defines the problem of Fine-grained Error Analysis for English Learners and introduces the FEANEL benchmark. Our extensive evaluation of various LLMs on FEANEL revealed significant challenges. While LLMs demonstrate foundational capabilities, they struggle with consistently applying fine-grained error categories to complex student errors, often lack the pedagogical nuance and conciseness of human feedback, and exhibit performance heavily influenced by prompt engineering, model scale, and internal reasoning structures.

Limitations

While our study provides the first large-scale benchmark and systematic evaluation for fine-grained error analysis in K-12 English writing, several practical constraints and design choices limit the scope of the current work. We summarize the most salient limitations below.

K-12 focus and domain coverage. All source essays are drawn from elementary and secondary school learners. This design serves our educational goal, yet inevitably narrows linguistic variety (e.g., genre complexity, domain-specific vocabulary, discourse structures) compared with adult or professional writing. Consequently, models that perform well on FEANEL are not guaranteed to generalize to university learners, workplace communication, or other L2 populations. Extending the dataset to additional age groups, proficiency levels, and register types is a promising next step.

English-only taxonomy. Our error taxonomy is tailored to English morpho-syntax and the curricular requirements of the Chinese K-12 context. Error categories and severity rubrics may not transfer directly to other target languages or educational standards. Multilingual validation and possible language-specific extensions will be required before FEANEL can serve broader data-centric AI research in second-language learning.

Reference-based automatic metrics. We evaluate error detection, categorization, and explanation quality primarily with reference-based metrics. Although these metrics allow large-scale reproducible benchmarking, they can over-penalize legitimately different but pedagogically useful feedback, and may not fully capture fluency, readability, or learner uptake. Follow-up work should incorporate rubric-based human ratings or preference learning to complement reference matching.

Ethics Statement

Every essay in FEANEL was scrubbed of personally identifiable information. We also ensure that no infringement or unethical behavior occurs during the dataset construction. Experienced teachers involved in the data annotation process were paid $10 - $20 per hour, which is well above local minimum wage. To maintain high-quality annotations, we developed a detailed annotation manual and conducted a pre-annotation trial, ensuring that annotators achieved at least 90% accuracy before the formal annotation process. Any annotator failing to meet this threshold was retrained or replaced. The essay topics and texts are generally concerned with daily life. Therefore, the new research direction and tasks we propose will not cause harm to human society and education applications.

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A Details of Dataset Construction

A.1 Error Type Taxonomy

We illustrate our constructed error type taxonomy in Figure 3. We stipulate the priority of error types according to their top-to-bottom positions in Figure 3. For instance, Case Error is assigned the lowest priority, while Sentence Redundancy Error holds the highest. In particular, Punctuation Error is prioritized between Contraction Error and Determiner Error due to its ubiquity. Therefore, when encountering an edit involving a Punctuation Error and a Determiner Error, models should classify it as a Determiner Error.

Definitions and examples of all error types in our proposed taxonomy are listed as follows:

(01) Case Error: Incorrect use of uppercase or lowercase letters. Example: Writing "paris" instead of "Paris."

(02) Space Error: Missing necessary spaces between words or having extra spaces. Example: Writing "tothelibrary" instead of "to the library."

(03) Spelling Error: The spelling of a word does not conform to standard norms. Note that both British and American spellings are considered correct and should not be classified as spelling errors. Example: Writing "recieve" instead of "receive"; "definately" instead of "definitely."

(04) Contraction Error: Incorrect use of word contractions. Example: Writing "isnt" instead of "isn't."

(05) Punctuation Error: Misuse or omission of punctuation marks in writing. For example,

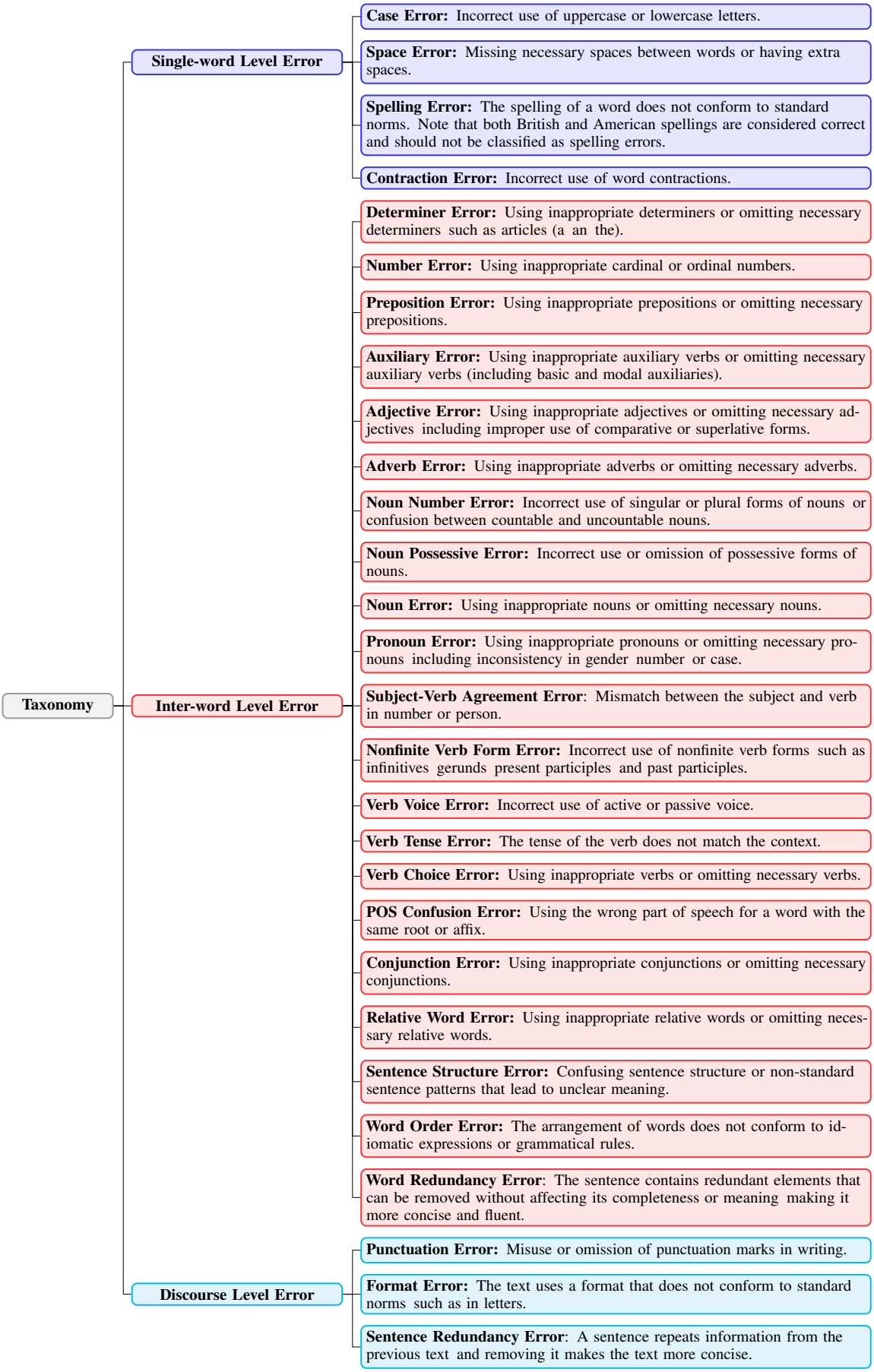


Figure 3: Taxonomy of Error Analysis for English Writing.

two or more independent clauses are improperly joined without correct punctuation or conjunctions, or sentence components that should be joined are separated into independent sentences. Example: Writing "He sings children's songs he is an excellent musician" instead of "He sings children's songs. He is an excellent musician."

(06) Determiner Error: Using inappropriate determiners or omitting necessary determiners, such as articles (a, an, the). Example: Writing "She has cat" instead of "She has a cat."

(07) Number Error: Using inappropriate cardinal or ordinal numbers. Example: Writing "two place" instead of "second place."

(08) Preposition Error: Using inappropriate prepositions or omitting necessary prepositions. Example: Writing "good in math" instead of "good at math."

(09) Auxiliary Error: Using inappropriate auxiliary verbs or omitting necessary auxiliary verbs (including basic and modal auxiliaries). Example: Writing "should sing well" instead of "can sing well."

(10) Adjective Error: Using inappropriate adjectives or omitting necessary adjectives, including improper use of comparative or superlative forms. Example: Writing "more taller" instead of "taller."

(11) Adverb Error: Using inappropriate adverbs or omitting necessary adverbs. Example: Writing "runs quick" instead of "runs quickly."

(12) Noun Number Error: Incorrect use of singular or plural forms of nouns, or confusion between countable and uncountable nouns. Example: Writing "many book" instead of "many books."

(13) Noun Possessive Error: Incorrect use or omission of possessive forms of nouns. Example: Writing "Johns book" instead of "John's book."

(14) Noun Error: Using inappropriate nouns or omitting necessary nouns. Example: Writing "The book is on the table" instead of "The book is on the shelf."

(15) Pronoun Error: Using inappropriate pronouns or omitting necessary pronouns, including inconsistency in gender, number, or case. Example: Writing "Everyone should bring their own lunch" instead of "Everyone should bring his or her own lunch."

(16) Subject-Verb Agreement Error: Mismatch between the subject and verb in number or person. Example: Writing "The list of items are" instead of "The list of items is."

(17) Nonfinite Verb Form Error: Incorrect use of nonfinite verb forms, such as infinitives, gerunds, present participles, and past participles. Example: Writing "suggested to go" instead of "suggested going."

(18) Verb Voice Error: Incorrect use of active or passive voice. Example: Writing "was ate" instead of "was eaten."

(19) Verb Tense Error: The tense of the verb does not match the context. Example: Writing "Yesterday, I go" instead of "Yesterday, I went."

(20) Verb Choice Error: Using inappropriate verbs or omitting necessary verbs. Example: Writing "tried to visit" instead of "decided to visit."

(21) PoS Confusion Error: Using the wrong part of speech for a word with the same root or affix. Example: Writing "beauty singer" instead of "beautiful singer."

(22) Conjunction Error: Using inappropriate conjunctions or omitting necessary conjunctions. Example: Writing "I wanted to go, and I was tired" instead of "I wanted to go, but I was tired."

(23) Relative Word Error: Using inappropriate relative words or omitting necessary relative words. Example: Writing "where I was born in" instead of "in which I was born."

(24) Sentence Structure Error: Confusing sentence structure or non-standard sentence patterns that lead to unclear meaning. Example: Writing "The book on the table which I read yesterday" instead of "The book which I read yesterday is on the table."

(25) Word Order Error: The arrangement of words does not conform to idiomatic expressions or grammatical rules. Example: Writing “older three years” instead of “three years older.”

(26) Word Redundancy Error: The sentence contains redundant elements that can be removed without affecting its completeness or meaning, making it more concise and fluent. Example: Writing “returned back” instead of “returned.”

(27) Format Error: The text uses a format that does not conform to standard norms, such as in letters. Example: Writing “Dear Sir, I am writing to you...” instead of “Dear Sir,\n I am writing to you....”

(28) Sentence Redundancy Error: A sentence repeats information from the previous text, and removing it makes the text more concise. Example: Writing “I went to the store. I went to the store to buy milk” instead of “I went to the store to buy milk.”

(29) Other Error: Errors that do not fall into the above categories. Example: Non-sense sentences like “I look like beauty as famous do.”

A.2 Details of Error Severity

Error severity in the proposed dataset is rated from 1 (trivial) to 5 (extremely serious).

- 1 point (trivial): Minor issues like spelling or punctuation that don’t affect understanding.

  Example: "I have a friand who likes football." (*friand* → *friend*)

- 2 points (minor): Errors like verb tense or simple subject-verb disagreement that don’t alter the main meaning.

  Example: "He go to school every day." (*go* → *goes*)

- 3 points (moderate): More complex errors not easy to understand, such as clause misuse.

  Example: "This is the book that I told you about it." (remove *it*)

- 4 points (serious): Multiple issues or confusing structure that hinder understanding.

  Example: "Yesterday I go store and bought some apples." (*go store* → *went to the store*)

- 5 points (extremely serious): Errors that make the sentence incomprehensible, often due to serious word misuse or structural issues.

  Example: "My brother are play hap." (*are play hap* → *is playing happily*)

A.3 Error Type Distribution

The distribution of error types across elementary and secondary school student essays in Figure 4 reveals that the error distributions are quite similar. Key error categories such as Punctuation Error, Spelling Error, Verb Tense Error, Word Redundancy Error, Determiner Error, and Preposition Error each account for over 5% of the total errors observed in both elementary and secondary school essays. These represent persistent challenges for K-12 English language learners. However, notable divergences also exist. For instance, Subject-Verb Agreement errors are proportionally more prevalent in the writing of elementary school students, which is consistent with typical language acquisition trajectories. Essays from secondary school students tend to exhibit a higher proportion of errors classified under the “Other” category. This suggests a more pronounced long-tail effect in their error patterns, possibly due to their engagement with more complex linguistic structures and vocabulary, leading to a wider variety of less common errors.

B Evaluation Details and Prompts for FEANEL

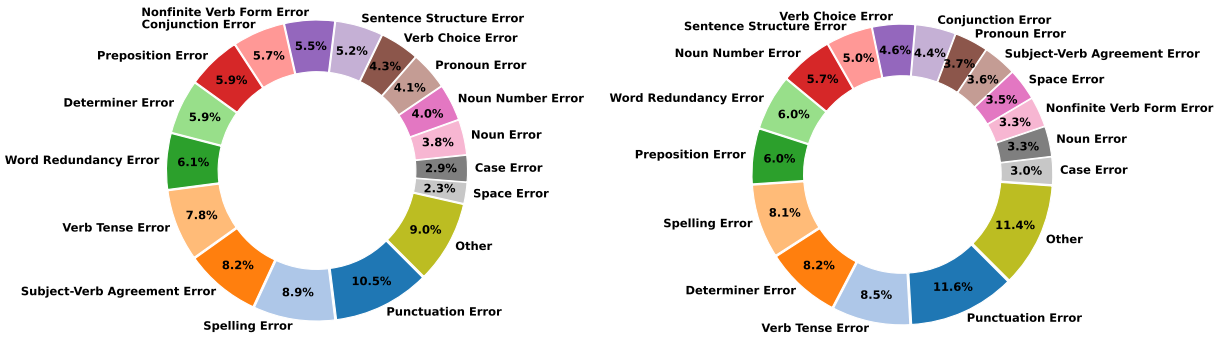
Evaluation Details. For closed-source or large models, we interact with the models through their respective APIs, ensuring consistency in input formatting and evaluation protocols. For the open-source models with parameter sizes less than 8B, we deploy them locally on NVIDIA A800 GPUs, leveraging their fine-tuned versions for conversational tasks. Each model is evaluated using identical prompts and settings to ensure fair comparisons. We set the `temperature` to 0.6 and `top_p` to 0.95.

Prompts. Our designed prompts are shown in Figure 5 and Figure 6.

C Extra Results

C.1 Performance on Each Error Type

A more granular examination of model performance across individual error categories is shown in Figure 7. LLMs generally achieve high classification accuracy on frequent and structurally simple



(a) Error type distribution of elementary essays.

(b) Error type distribution of secondary essays.

Figure 4: Error type distribution of FEANEL. We illustrate the most frequent 16 error types out of totally 29 error types due to the space limit and present the remaining error types as "Other".

Prompt for the `Zero-shot-naive` setting

You are an experienced English K-12 teacher, specializing in providing accurate and relevant educational feedback for writing errors in essays. To ensure accuracy and relevance, adhere to these principles:
1. Analyze each given edit one by one. Maintain the exact number of edits and make sure the edit index is correct.
2. Don't alter the error and correction content in any case.
3. Specify a single error type, a severity, and a description for each edit. If an edit involves multiple errors, you must predict only one error type with the highest priority order (see below). However, when describing, you must provide a detailed explanation for each error type and use numbering such as ①, ②, and semicolons to separate the descriptions of different error types.
4. Error severity is rated from 1 (trivial) to 5 (extremely serious).
5. The error description must target the predicted error type, highlight the violated semantic rules and relevant knowledge, and explain the given correction and its rationale.
6. Use specific symbols to emphasize evidence words and correction methods: (1) Evidence words from the error sentence are enclosed in ⟨⟩. (2) Correction methods from the correct sentence are enclosed in [].
7. Predict a single error type for an edit based on the following error taxonomy. Directly generate the name of the error type without serial number, e.g., "Preposition Error." Don't generate any other error types not included in the taxonomy.

Error Taxonomy:
(01) Case Error
...

8. Output strictly in the following JSON format.
{JSON Format Instruction}

Now you should deal with the following input and output a single JSON output.
{Input}

Figure 5: Prompt for the `Zero-shot-naive` setting

Prompt for the `One-shot-detailed` setting

You are an experienced English K-12 teacher, specializing in providing accurate and relevant educational feedback for writing errors in essays. To ensure accuracy and relevance, adhere to these principles:
1. Analyze each given edit one by one. Maintain the exact number of edits and make sure the edit index is correct.
2. Don't alter the error and correction content in any case.
3. Specify a single error type, a severity, and a description for each edit. If an edit involves multiple errors, you must predict only one error type with the highest priority order (see below). However, when describing, you must provide a detailed explanation for each error type and use numbering such as ①, ②, and semicolons to separate the descriptions of different error types.
4. Error severity is rated from 1 (trivial) to 5 (extremely serious).
- 1 point (trivial): Minor issues like spelling or punctuation that don't affect understanding.
Example: "I have a friand who likes football." (friand -> friend)
- 2 points (minor): Errors like verb tense or simple subject-verb disagreement that don't alter the main meaning.
Example: "He go to school every day." (go -> goes)
- 3 points (moderate): More complex errors not easy to understand, such as clause misuse.
Example: "This is the book that I told you about it." (remove it)
- 4 points (serious): Multiple issues or confusing structure that hinder understanding.
Example: "Yesterday I go store and bought some apples." (go store -> went to the store)
- 5 points (extremely serious): Errors that make the sentence incomprehensible, often due to serious word misuse or structural issues.
Example: "My brother are play hap." (are play hap -> is playing happily)
5. The error description must target the predicted error type, highlight the violated semantic rules and relevant knowledge, and explain the given correction and its rationale.
6. Use specific symbols to emphasize evidence words and correction methods: (1) Evidence words from the error sentence are enclosed in ⟨⟩. (2) Correction methods from the correct sentence are enclosed in [].
7. Predict a single error type for an edit based on the following error taxonomy. Directly generate the name of the error type without serial number, e.g., "Preposition Error." Don't generate any other error types not included in the taxonomy.

Error Taxonomy:
(01) Case Error: Incorrect use of uppercase or lowercase letters. Example: Writing "paris" instead of "Paris".
...

8. Here provides an input and output example strictly in JSON format.
{Example}

Now you should deal with the following input and output a single JSON output.
{Input}

Figure 6: Prompt for the `One-shot-detailed` setting

Setting	Pre-exp.	Classification				Severity		Explanation					
		Acc↑		F_1↑		MAE↓		BLEU↑		METEOR↑		ROUGE↑	
Zero-shot-naive	✗	61.74	66.79	46.55	52.67	0.87	0.77	**1.35**	**1.19**	17.87	**17.58**	**24.29**	**23.02**
	✓	**62.04**	**67.56**	**48.04**	**54.51**	**0.85**	**0.76**	1.31	1.07	17.97	17.32	24.37	22.99
One-shot-detailed	✗	**66.57**	72.02	**52.97**	57.66	0.78	**0.66**	2.46	**2.16**	19.96	19.70	28.41	26.13
	✓	65.90	**72.62**	51.46	**59.33**	**0.70**	**0.66**	**2.61**	2.05	**20.42**	**19.76**	**29.14**	**26.50**

Table 4: Ablation results of prediction order. We color the results of the secondary domain.

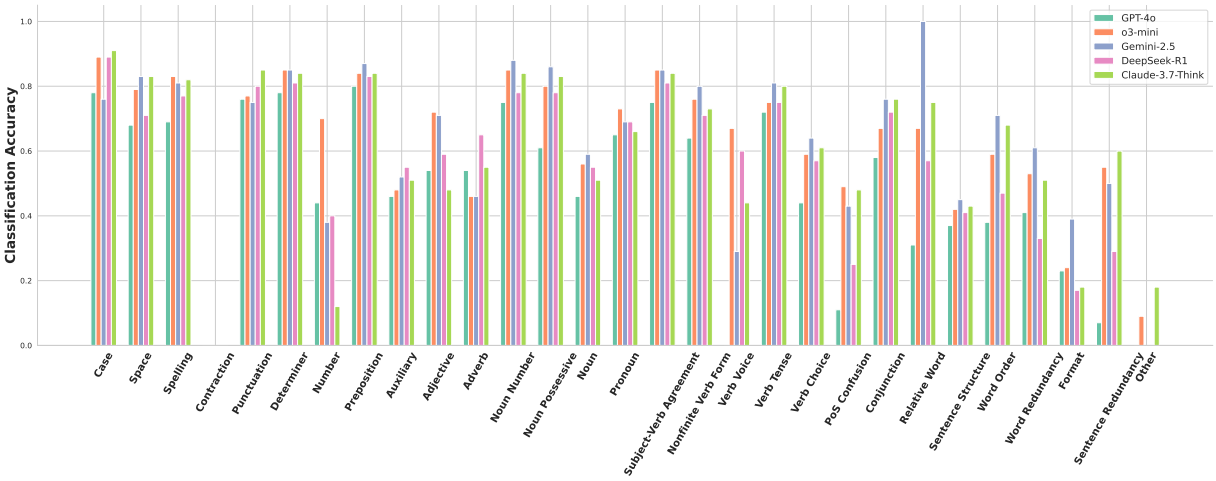


Figure 7: Classification accuracy of GPT-4o, o3-mini, Gemini-2.5-pro, DeepSeek-R1, and Claude-3.7-Think. We list the accuracy of all 29 error types.

error types such as Case Error, Space Error, and Spelling Error. However, their performance significantly degrades on less frequent or long-tail categories and those requiring deeper linguistic understanding or contextual reasoning. These challenging types include Contraction Error, Number Error, Auxiliary Verb Error, Part-of-Speech (PoS) Confusion Error, Sentence Structure Error, and Format Error. This disparity underscores a key deficiency in current LLMs: an incomplete or insufficiently nuanced grasp of the full spectrum of error types defined within our comprehensive taxonomy, particularly those that are either rare in typical training data or inherently more complex and semantically subtle, calling for future improvement.

C.2 Effect of Prediction Order

To investigate the influence of the generation sequence on model performance, we conducted an ablation study by altering the prediction order of the three main components. Our default approach, termed *Post-explaining*, predicts elements in the sequence: Error Severity → Error Type → Error Explanation. We compared this against an alternative, *Pre-explaining*, which follows the order: Error Explanation → Error Severity → Error Type. All experiments for this ablation were performed using the GPT-4o model, and the results are detailed in Table 4. In the `Zero-shot-naive` setting, the *Pre-explaining* order (generating the explanation before the error type) leads to improved performance in Error Classification and Error Severity Rating. However, this comes at the cost of reduced quality in the Error Explanation itself. This observation aligns with the intuition that outputs generated earlier in a sequence can serve as valuable contextual information for subsequent steps. Interestingly, this trend reverses in the `One-shot-detailed` setting, where the *Pre-explaining* model demonstrates nearly superior performance across all three aspects. We attribute this significant shift to the influence of the in-context demonstration. The demonstration likely provides a strong template or implicit guidance on how to structure the thought process when generating an explanation first effectively, and then coherently deriving the error type and severity from that explanation.