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Abstract

Writing has long been considered a hallmark of human intelligence and remains a pinnacle task for artificial intelligence (AI) due to the intricate cognitive processes involved. Recently, rapid advancements in generative AI, particularly through the development of Large Language Models (LLMs), have significantly transformed the landscape of writing assistance. However, underrepresented languages like Arabic encounter significant challenges in the development of advanced AI writing tools, largely due to the limited availability of data. This scarcity constrains the training of effective models, impeding the creation of sophisticated writing assistance technologies. To address these issues, we present Gazelle, a comprehensive dataset for Arabic writing assistance. In addition, we offer an evaluation framework designed to enhance Arabic writing assistance tools. Our human evaluation of leading LLMs, including GPT-4, GPT-4o, Cohere Command R+, and Gemini 1.5 Pro, highlights their respective strengths and limitations in addressing the challenges of Arabic writing. Our findings underscore the need for continuous model training and dataset enrichment to manage the complexities of Arabic language processing, paving the way for more effective AI-powered Arabic writing tools.

1 Introduction

Writing is an essential skill for both individuals and professionals, requiring a long-term commitment to mastery that can span years of continuous learning and refinement (Flower and Hayes, 1980; Du et al., 2022). The distinct cognitive processes involved in writing underscore the significant importance and complexity of writing as a task. Consequently, in the fields of AI and natural language generation (NLG), writing is considered a hallmark of human intelligence, and researchers have long viewed it as a pinnacle task for

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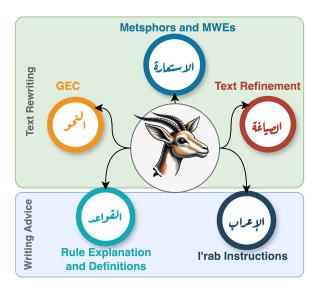


Figure 1: Task categorization for *Gazelle*. **GEC**: Grammatical Error Correction (التصحيح النحوي); **MWEs**: Multi-Word Expressions.

their studies (Ippolito et al., 2022; Urmeneta and Romero, 2024; Chen et al., 2024). In recent years, the landscape of writing assistance has been transformed by rapid advances in generative AI, particularly through the development of LLMs (Ippolito et al., 2022; Lee et al., 2024). These neural models, trained on the intricacies of language by processing vast amounts of text, have led to the creation of AI-powered tools designed to provide comprehensive writing assistance across a wide range of tasks (Zhang et al., 2022; Chowdhery et al., 2023). Models like GPT-3 and GPT-4 (Brown et al., 2020; Achiam et al., 2023) have demonstrated impressive capabilities in both understanding and generating text (Bubeck et al., 2023). These LLMs have significantly expanded the potential for "Human-AI co-writing," where AI systems provide flexible support that extends far beyond simple grammar and spell-checking to polishing texts and generating completely new content, significantly enhancing writing assistance for diverse writing tasks (Li et al., 2024).

However, underrepresented languages like Arabic often face substantial challenges in developing advanced AI tools, including writing assistance, largely due to the scarcity of relevant training data. In this work, we seek to bridge this gap by introducing Gazelle, a dataset specifically curated for Arabic writing, designed to advance the development of AI-powered writing tools for underrepresented languages. Gazelle is a manually curated instruction-style dataset crafted in both English and Arabic and organized around two primary themes. The first theme, text rewriting, aims at supporting learners in rewriting their texts across different linguistic levels. This encompasses (i) Grammatical Error Correction (GEC) at various levels such as orthographic, morphological, syntactic, and semantic with catgeories beyond those proposed in the Arabic Learner Corpus (ALC) (Alfaifi and Atwell, 2014) adopted in previous works. Text rewriting also involves corrections of deeper semantic levels beyond traditional GEC that cover (ii) Metaphors and Multi-word Expressions (MWEs) and (iii) Text Refinement, which focuses on improving texts by replacing dialectal sequences with their equivalent standard forms and fixing poor language.

The second theme, **writing advice**, covers (*iv*) *Rule Explanation and Definitions* as well as (*v*) *I'rab*. In Arabic, I'rab or declension refers to the variation in a word's form that indicates its grammatical case and role within a sentence. In *Gazelle*, the I'rab category guides learners through the different grammatical roles within a text, such as identifying when a word takes on a nominal case due to its role as a subject in a sentence. Across its various categories, *Gazelle* also provides explanations for the suggested corrections. Figure 1 outlines the main tasks covered in *Gazelle*, and Figure 2 illustrates each of these tasks.

Our contributions can be summarized as follows: (1) We introduce a comprehensive, manually curated dataset specifically for Arabic, covering two different writing themes across five distinct tasks. (2) We expand the Arabic Learner Corpus (ALC) (Alfaifi and Atwell, 2014) error taxonomy by developing a fine-grained classification, including adding sub-classes and detailed sub-subclasses under the main error categories. Furthermore, we generate synthetic data from the Arabic Tree Bank (ATB) (Maamouri et al., 2004) that aligns with our new classification and sub-classes for specific error types in the ALC error taxonomy. (3) We conduct a comparative evaluation of current leading LLMs —GPT-4 (Brown et al., 2020), GPT-4*o* (Achiam et al., 2023), Cohere Command R+,¹ and Gemini 1.5 Pro (Reid et al., 2024)—focusing on their capabilities in different Arabic writing tasks.

The rest of this paper is organized as follows: In Section 2, we provide an overview of related work. Section 3 introduces our manually curated datasets for Arabic writing assistance. In Section 4, we provide a comparison of Gazelle with other GEC datasets. Section 5 presents our evaluation of the frontier LLMs on Arabic writing tasks. We also detail our human evaluation methodology and results. We conclude in Section 6.

2 Related Work

LLMs for Writing Assistance. The advent of LLMs and their enhancement through data augmentation and instruction tuning have significantly advanced automated writing assistance tools (Wei et al., 2022; Ouyang et al., 2022; Raheja et al., 2023). Models trained on extensive datasets of human-written instructions, using methods like instruction fine-tuning, have proven to enhance their ability to generalize across various tasks by leveraging large, diverse sets of instructional data (Zhang et al., 2023). Models like FLAN-T5 (Chung et al., 2024) and GPT-4 (Bubeck et al., 2023; Peng et al., 2023; Chung et al., 2024) demonstrate the progress and capabilities of incorporating a wide array of tasks during fine-tuning to achieve robust performance and adaptability in various writing applications (Sanh et al., 2021; Liu et al., 2022). We provide detailed examples of recent advancements in instruction-tuned models and their application on writing assistance in Appendix A.

Progress in Arabic Writing Tasks. Arabic writing tasks are complex due to its linguistic and morphological diversity, compounded by orthographic ambiguities from optional diacritics and dialectal variations (Abdul-Mageed et al., 2020; Belkebir and Habash, 2021a). Despite these challenges, significant progress has been made in terms of model development and dataset developments across different writing tasks such as GEC (Zaghouani et al., 2014; Habash and Palfreyman, 2022; Kwon et al.,

¹https://docs.cohere.com/docs/command-r-plus

Task	Error Class	Incorrect Sentence	Corrected Sentence	Explanation
GEC	Morphology	سجلت وحدات الحماية المدنية 999. حادث مرور أدت إلى وفاة 32 شخصا.	سجلت وحدات الحماية المنية 999. حادث مرور أدى إلى وفاة 32 شخصا.	الخطأ في الفعل أدى، يعبر عن حدث أو موقف مذكر لذلك يجب أن يكون خالتي من تاء التأنيث.
Metaphors	Metaphors	كان نقده <mark>كالملح</mark> في العسل.	کان نقده کالسم في العسل.	الخطأ في استخدام التعبير كالملح في العسل، مما يغير المعنى المقصود من شيء ضار متنكر كشيء حلو إلى شيء غير متناسب ولكنه أقل ضررًا.
Multi Word Expressions	MWEs	وقد لمح بذلك إلى قيادة "الموساد المخابرات الإسرائيلية التي تريد أن تأخذ علي ر <mark>أسها</mark> مسؤولية الحملة الدولية إيران باعتباره موضوعاً أمنيا.	وقد لمع بذلك إلى قيادة الموساد المخابرات الإسرائيلية التي تريد أن تأخذ على عاتقها مسؤولية الحملة الدولية ضد إيران باعتباره موضوعاً أمنيا.	الخطأ في كلمة بطيء: كتبت الهمزة المتطرفة على الياء لأن حركة الحرف الذي قبلها الكسرة.
Text Refinement	Style Transfer	وأنت تعرف جيداً، ولا عارف أن أصابعنا تحت ضرسه.	وأنت تعرف جيدًا، وتعرف أن حياتنا بين يديه.	(أصابعنا تحت ضرسه) مصطلح مصري عامي بمعنى أنهم تحت رحمته أو تحكمه، ولا يصح كتابته في الفصحى.
l'rab	Declension	اعرب الجملة التالية إعرابا ً كاملا:الجملة:راقب ً الوالد أولاده وهم يلعبون.	مبتداً. ي آخره خبر	بكل تلكيد، إليك إعراب الجملة بالكامل: راقب:فعل ماض ميني على القتح. الوالد:فاعل مرفرغ وملاحة رفعه الضمة، بيني في محل جر مخ الواق:والحال و(هم)ضعير رفع منفصل ميني في محل رفع ليفعون:فعل مضارع مرفوغ وعلامة رفعة شيت نين الإعراب فر البتدا (هم)والجملة الاسمية من(هم يلعبون)في محل نصب حال

Figure 2: Examples of corrections and explanations for various Arabic writing tasks included in *Gazelle*. For instructions in English, see Table D.1

2023), text simplification (Hazim et al., 2022; Alhafni et al., 2024) and text summarization (Al-Maleh and Desouki, 2020; Lagrini and Redjimi, 2021). Further details about the progress in Arabic writing tasks are provided in Appendix A.

Explainable Writing Systems. Recent advancements in explainable writing systems have greatly improved the transparency and alignment of tools with instructional goals across various tasks. In GEC, tools like ERRANT (Bryant et al., 2017a) provide clear error annotations and edit boundaries, enhancing users' understanding of grammatical mistakes. In text simplification and feedback generation, systems strive to offer precise and relevant explanations, ensuring that users receive actionable and comprehensible feedback (Agarwal, 2022). These efforts highlight the importance of creating tools that deliver understandable insights and ensure alignment with instructional goals (Kunz and Kuhlmann, 2024). We provide further details on the progress of explainable writing systems in Appendix A. However, to the best of our knowledge, no prior work has investigated instruction-tuned LLMs' ability to provide explanations and definitions for diverse writing tasks, organized around distinct pedagogical themes.

3 Gazelle

As mentioned in Section 1, *Gazelle* comprises two main themes, text rewriting and writing advice, across *five* distinct types of writing assistance instructions that we manually curate. *Gazelle* encompasses parallel data with instructions crafted in both Arabic and English, covering both input and output, allowing users to fine-tune models for these various tasks bilingually. Except for the I'rab and Arabic grammatical rules and definitions datasets, we manually translate the Arabic explanations and instructions into English. To ensure thorough coverage, we curate instructions for each of these tasks separately from several publicly available online sources.² Table 1 presents the statistics for text rewriting tasks, while Table 2 provides statistics for tasks related to writing advice. Examples of these tasks are illustrated in Figure 2. For the English translations of the GEC explanations and definitions task dataset in Table 1, we leverage GPT- $4o^3$ to accurately translate the manually curated Arabic content. This process involved iteratively prompting GPT-40 and refining the generated through multiple rounds of manual review to ensure the translations were both accurate and contextually appropriate, allowing us to produce high-quality English translations. We explain each of our instruction categories next.

3.1 Text Rewriting

3.1.1 GEC

Fine-Grained Error Taxonomy. The original ALC error taxonomy comprises 29 error tags categorized under five main error classes: *Orthographic, Morphology, Syntax, and Semantics.* Additionally, Belkebir and Habash (2021b) introduced two more error classes: *Split* and *Merge.* Building upon this foundation, we expand the orig-

 $^{^{2}}$ See Appendix G.2 for example sources we use.

³https://openai.com/index/hello-gpt-40/

Task	Category	Source	Language	Total
	Orthographic	Online Sources		637
	Syntax	Online Sources		377
	Semantic	Online Sources		362
GEC	Morphology	Online Sources	Arabic	55
GEC	Punctuation	Online Sources	Alabic	28
	Split	ATB		100
	Merge	ATB		100
GEC_ATB		ATB	Arabic	1,433
GEC + Definitions		Online Sources	Arabic	290
GEC + Explanations		Online Sources	Arabic	1,659
MWE		PARSEME dataset	Arabic	00
			English	98
Text Refinement		In-house Project	Arabic	770
			English	//0

Table 1: Data statistics for *text rewriting* tasks.

Task	Source	Language	Total
Rule Explanations & Definitions	Online Sources Online Sources	Arabic English	1,445 1,005
I'rab	Online Sources	Arabic	1,090

Table 2: Data statistics for writing advice tasks.

inal ALC error taxonomy to develop a fine-grained grammatical error taxonomy.

Our proposed taxonomy introduces two more sub-classes to the original ALC error categories: Closed Class Error under Syntax and Special Expression Error under Semantic, bringing the total to 31 error tags. Closed class errors address issues with closed class items, such as the five nouns, the five verbs, and pronouns. Special expression errors covers the use of collocations, multi-word expressions, and other commonly misused terms Additionally, each of our new error categories include several sub-subclasses. For example, the sub-classs Number under Syntax which pertains to the correct use of singular, dual, and plural forms in nouns, verbs, and pronouns is further divided into several sub-subclasses. Our newly-developed categorization scheme incorporates extensive knowledge of Arabic grammar, aiming to provide users with not only the category of grammatical error but also its sub- and sub-subclasses. Table D presents a detailed overview of all the newly introduced categories. It comprises 7 classes, each with an average of 9 sub-classes.⁴

GEC Instructions. We develop a set of 3,382 bilingual instructions for GEC, based on our newly extended error taxonomy. This comprehensive taxonomy includes a wide range of error sub-classes and sub-subclasses, aiding identification of specific

errors. We manually curate these sentences from various Arabic learning online sources to reflect the detailed error categories in our extended taxonomy. Each sentence pair includes grammatical errors along with their corrected versions and explanations, as shown in Table D.1. Examples of these detailed error sub-classes and their coverage are provided in Appendix C.

GEC Error Explanations. We introduce a dataset containing detailed explanations for each type of error sub-class and sub-subclass, comprising a total of 1,659 entries sourced from websites and books. This dataset enables users not only identify the type of error but also understand the explanations behind it. The explanations are provided in both Arabic and English. We provide examples of these detailed error explanations in Appendix C.

ATB Synthetic Data. ATB is a collection of texts annotated for morphosyntax with English glosses. We utilize all parts of the ATB to generate 100 examples with a total of 1,633 covering the *Orthographic*, *Syntax*, *Split*, *Merge*, *Morphological*, and *Punctuation* error classes along with their subclasses. More details on the examples generated are provided in Appendix C.

Generating synthetic data from ATB allows us to efficiently acquire real-world data with human labels. We then use templates to format these examples into an instruction format.

For each error type, we follow specific rules that dictate how errors are created, ensuring consistency throughout the process. We prioritize aligning our error generation with those made by humans, rather than relying on random or arbitrary variations. For instance, with OM (Orthographic Missing) errors, where characters are missing, we simulate typical human mistakes by deliberately omitting characters that are commonly omitted in real-world usage. Appendix E provides detailed information on the methodology we follow to generate these synthetic errors from ATB.

3.1.2 Metaphors and MWEs

MWEs are diverse and arbitrary word combinations that co-occur frequently. They include idiomatic phrases, compound words, and other constructions with varying levels of transparency and fixedness, all sharing the characteristic of crossing word boundaries (Sag et al., 2002). Our dataset comprises 330 sentences featuring incorrect usage

⁴We exclude all error tags within the *Other* error class (e.g., OO, XO, SO, MO) to avoid complications.

of metaphors or MWEs, along with corrected versions and explanations of the errors. The sentences with metaphors were manually collected from online resources. For MWE sentences, we randomly selected 98 sentences from the PARSEME dataset (Mohamed et al., 2022) a collection of verbal multiword expressions in Arabic. To generate sentences with errors, we use GPT-40 to modify correct metaphors and MWEs into incorrect ones. We provide the correct sentence and instruct it to alter the metaphor or MWEs.

3.1.3 Text Refinement

Text Refinement refers to improving the quality of MSA by addressing informal or colloquial words in a text or by enhancing texts written in poor language. We create a set of instructions comprising a total of 770 sentences (we collect these sentences from an in-house project) focused on detecting informal words and improving text quality, along with explanations of these errors. Examples regarding this task can be found in Appendix C.

3.2 Writing Advice

3.2.1 Rule Explanation and Definitions

We develop a bilingual dataset consisting of 2, 450 examples that provide explanations and definitions of grammatical rules in both Arabic and English. This dataset covers a wide range of topics in Arabic grammar, from basic concepts such as nouns, verbs, negation, and sentence structures to advanced topics like verb inflections, formations, and stylistic nuances. Each entry offers comprehensive definitions and illustrative examples to enhance understanding. Contextual examples are also included to demonstrate the practical application of these rules. Illustrative examples can be found in Figure D.1.

3.2.2 I'rab

I'rab, or declension, is a term in Arabic that refers to the system of nominal, adjectival, or verbal suffixes used to mark the grammatical case of a word. These suffixes helps identify the function of a word within a sentence (Hamani, 2014). We design 1,090 instructions that provide the full I'rab of sentences, covering a wide range of topics in Arabic grammar, as detailed in Figure D.1.

4 Gazelle in Comparison

The QALB dataset comprises manually corrected Arabic texts, including MSA commentaries from Aljazeera by native speakers (L1) and texts by non-native learners (L2)(Rozovskaya et al., 2014; Mostefa et al., 2015). The ZAEBUC corpus, on the other hand, contains essays written by first-year students at Zayed University in the UAE(Habash and Palfreyman, 2022). While both the QALB and ZAEBUC corpora include multiple errors per sentence or paragraph, facilitating automatic evaluation, our datasets are curated with a different focus.

We manually curate the *Gazelle* dataset to target specific error types within the ALC error taxonomy by extending the existing error categories and incorporating our own extended categories. Each sentence, sourced from various Arabic learning online sources, represents a specific subclass or sub-subclass of our extended error taxonomy and contains only one type of error along with explanation of this type of error. This targeted approach makes our dataset particularly useful for learners aiming to understand and correct specific types of errors. We provide a comparison of *Gazelle* dataset to the QALB and ZAEBUC corpora in Appendix F.1

5 Evaluating Leading LLMs on Gazelle

We evaluate *Gazelle* on current leading LLMs, namely GPT-4, GPT-4*o*, Gemini 1.5 Pro, and Cohere Command R+, to assess their capabilities across our proposed tasks in Arabic. We test the models under a zero-shot setting (Sanh et al., 2021), allowing us to assess the models' inherent capabilities in handling our proposed writing tasks. For each task, we initially tested the prompts and iteratively refined a zero-shot prompt tailored to each subtasks. Further details on our prompt design process, along with examples used for evaluation, are provided in Appendix F.

5.1 Human Evaluation

We conduct human evaluation to assess the performance of the aforementioned LLMs on *Gazelle's* five subtasks. Developing evaluation criteria for these subtasks in Arabic writing was challenging due to the lack of existing standard measures. Consequently, we create a list of suitable measures for all subtasks and iteratively refine them. Each criterion was clearly defined to ensure both comprehensiveness and clarity.

For evaluation, we ask four native Arabic speakers to assess the models' performance by randomly sampling a subset of 20 sentences from each task,

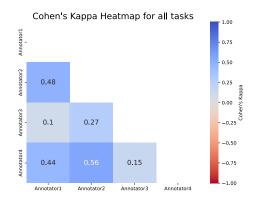


Figure 3: Overall inter-annotator agreement for human evaluation measured by Cohen's Kappa.

resulting in a total of 100 sentences. Annotators were then asked to evaluate the models' outputs for each task using the metrics we developed, which include *accuracy*, *clarity*, *helpfulness*, *appropriateness*, *correctness*, *consistency*, *depth* of explanation, *quality* of text refinement, *fluency*, and *relevance*. Each response was scored on a scale from 1 to 5, reflecting on how well it met the evaluation criteria. Detailed descriptions of the evaluation scales are provided in Appendix G.

We calculate the Cohen's Kappa scores for inter-annotator agreement among four annotators across all tasks. Figure 3 displays the overall interannotator agreement, which varies across annotator pairs, with some pairs showing moderate agreement and others showing slight to fair agreement. Individual inter-annotator agreements are provided in Appendix G.1.

5.2 Results

We present the results of our evaluation in Figure 4. The performance of each model on the outlined writing tasks is discussed below.

GEC and Explanation Tasks. For the GEC and explanation tasks, we evaluate the performance of the models based on three criteria: *accuracy*, *clarity*, and *helpfulness*. Figure 4a displays the evaluation result for this task.

Overall, GPT-4*o* demonstrates superior performance in the GEC task, excelling in all criteria. Cohere Command R+ and Gemini 1.5 Pro provide balanced results, whereas GPT-4, while maintaining a reasonable level of *clarity*, falls short in *accuracy* and *helpfulness*. **MWEs.** In the MWEs task, we evaluate the four models based on *clarity*, *appropriateness* of multi-word expressions, and *relevance*. Figure 4b shows result of the evaluation for this task. Overall, GPT-4o outperforms all models in the MWEs task, delivering the highest scores in all criteria. Both Cohere Command R+ and Gemini 1.5 Pro perform well, particularly in *clarity* and *relevance*, while GPT-4 lags in appropriateness but maintains reasonable levels of *clarity* and *relevance*.

Text Refinement. We evaluate the text refinement task based on *clarity*, *quality* of text refinement, and *fluency*. Figure 4c presents result of the evaluation for this task. GPT-4o excels in the Text Refinement task, leading with superior scores in *clarity*, *quality* of text refinement, and *fluency*. Both Cohere Command R+ and Gemini 1.5 Pro show balanced and consistent performance, while GPT-4 also performs well, particularly in *fluency*.

Grammatical Rules and Definitions. For this task, we evaluate the models based on three criteria: *clarity, consistency* with grammatical rules and definitions, and *depth* of explanation. Figure 4d illustrates the result for this task.

In summary, GPT-4*o* performs exceptionally in the grammatical rules and definitions task, scoring highest in all criteria. Gemini 1.5 Pro follows closely, offering strong and balanced performance. Cohere Command R+ also performs well, particularly in *clarity* and *depth*, while GPT-4 shows the lowest scores across all criteria.

I'rab. We evaluate the models on three criteria for the I'rab task: *clarity*, *helpfulness*, and *correctness* of I'rab. Figure 4e presents result of the evaluation for this task.

Overall, GPT-4*o* dominates the I'rab task with superior scores in *clarity*, *helpfulness*, and *correctness*. Cohere Command R+ also performs well, especially in *clarity* and *helpfulness*. Gemini 1.5 Pro shows balanced results, while GPT-4 has the lowest scores across all criteria.

5.3 Discussion

Cohere Command R+. Cohere Command R+ excels in delivering clear and helpful explanations,

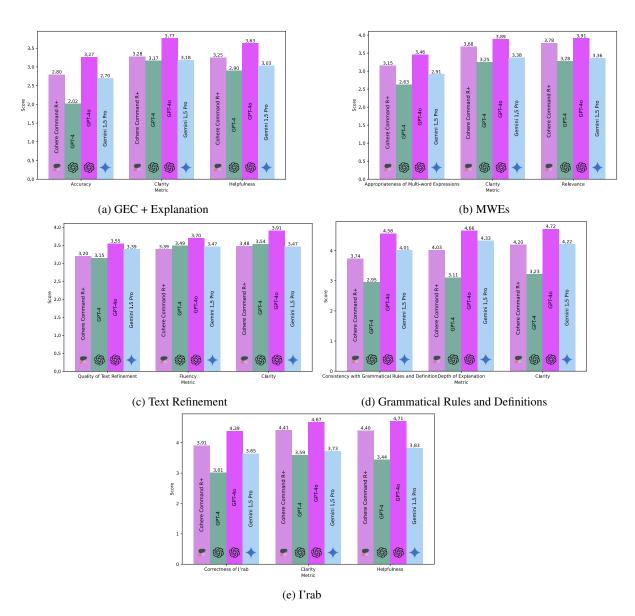


Figure 4: Results of human evaluation for four LLM models: GPT-4, GPT-4*o*, Cohere Command R+, and Gemini 1.5 Pro on five subtasks in *Gazelle*.

particularly in handling MWEs and I'rab writing tasks. It consistently offers understandable and relevant responses in these areas. However, its performance in GEC tasks is less robust, with lower *accuracy* and *correctness* compared to other models. We provide detailed statistical evaluation metrics for the five subtasks across all models in Table G.3

GPT-4. GPT-4 demonstrates the weakest overall performance among all the models evaluated. While it does provide reasonable *clarity* and *relevance* in its responses, it struggles with the *accuracy* and *depth* required for tasks such as GEC, explaining grammatical rules, and providing GEC explanation. It scores the lowest compared to the other models in these critrea. Although GPT-4's performance is stable, it does not excel in any specific task.

GPT-40. GPT-40 stands out as the topperforming model across all tasks. It consistently achieves the highest scores by demonstrating superior *clarity*, *correctness*, and *depth* in its responses. GPT-40 reliably provides the most *accurate*, *relevant*, and *helpful* outputs, making it the most effective model for comprehensive Arabic writing assistance. Its performance is robust and reliable, with minimal weaknesses observed.

Gemini 1.5 Pro. Gemini 1.5 Pro delivers a balanced and strong performance across all tasks.

It particularly excels in explaining grammatical rules and providing detailed and consistent responses. Although it performs well overall, it does not quite reach the high performance levels of GPT-40. In tasks involving MWEs and I'rab, Gemini 1.5 Pro shows room for improvement, where it is less effective compared to GPT-40.

5.4 Human Analysis of the Models

We outline insights from our human analysis, offering a detailed evaluation of how each model handles specific linguistic challenges across all tasks.

GEC and explanation task. Models frequently corrected sentences but occasionally struggled with accurate explanations or identifying all errors, highlighting their limitations in grasping Arabic grammar complexities. The task of applying grammatical rules and definitions revealed varying proficiency among the models, showcasing their differing capabilities in handling Arabic grammar.

MWEs and Metaphors. All models struggled with handling MWEs and metaphors. This difficulty was evident in models' ability to identify errors and provide accurate metaphors or MWEs, highlighting their inability to fully capture the linguistic richness of Arabic.

The complexity of handling MWEs and metaphors in Arabic stems from their nuanced and context-dependent nature. Unlike single-word expressions, MWEs and metaphors often convey meanings that cannot be directly inferred from the individual words. Furthermore, the cultural and contextual connotations embedded in Arabic expressions add another layer of difficulty for the models.

Text Refinement. In the text up-refinement task, a creative exercise, models showed diverse capabilities. Some excelled in enhancing stylistic elements such as GPT-4*o* and Gemini 1.5 Pro, while others focused on basic corrections as in the case of GPT-4.

I'rab. The I'rab task, requiring deep linguistic knowledge, revealed mixed abilities in applying these rules. Models like Cohere Command R+ and GPT-4*o* performed well, while others showed limitations in providing a fully correct I'rab of the sentences.

Overall, this analysis highlights the variability in model performance, showcasing each model's strengths in specific areas and their limitations in understanding and applying Arabic grammar and stylistic enhancements.

6 Conclusion

In this work, we present *Gazelle* a comprehensive dataset and evaluation framework to enhance Arabic writing assistance tools. Our manually fine-grained dataset incorporates five writing subtasks under two main themes. Our analysis uncovers both strengths and limitations of the most leading LLMs in tackling the unique challenges of Arabic writing. These insights highlight the need for continuous model training and dataset enrichment to address the complexities of Arabic language processing.

Our study showcases the varied capabilities of models in handling Arabic grammar and stylistic nuances, providing a foundational step towards more advanced 'Human-AI co-writing' tools for Arabic writing. Future research may include on expanding the dataset and integrating diverse linguistic features to develop robust and reliable models for mastering Arabic writing.

Overall, our work serves as a stepping stone towards creating more effective Arabic writing assistance tools and advancing the field significantly.

Limitations

We identify the following limitations in this work:

- The dataset may not encompass the full diversity of the Arabic language, including its many dialects and regional variations, limiting the generalizability of the results.
- The study focuses on zero-shot settings, which highlight models' inherent capabilities but not their performance with fine-tuning. Future work may include fine-tuning for enhanced performance.
- The human evaluation process is subjective and may be influenced by individual biases, particularly in tasks like text up-scaling and error explanation.
- The study evaluates four specific LLMs. As models evolve, re-evaluation will be necessary to maintain relevance in assessing their performance on Arabic writing tasks.

Ethics Statement

Encouraging research development and contributing to a collaborative research culture. Low-resource languages such as Arabic face significant hurdles in the development of advanced AI tools due to a scarcity of comprehensive datasets. This shortage hampers the ability to train effective models, limiting the creation of sophisticated writing assistance tools for these languages. Our current work aims to bridge this gap by introducing Gazelle, a dataset specifically curated for Arabic writing. This dataset is designed to support the development of AI-powered tools that can enhance Arabic language processing. By providing this diverse and detailed dataset, we aspire to stimulate further research and development in Arabic AI tools, fostering a collaborative effort to overcome the challenges faced by low-resource languages.

Advancing Pedagogical Approaches in Arabic Writing. With the growing interest in enhancing language proficiency, the accuracy and effectiveness of written communication have become essential for both native speakers and second language learners. LLMs are increasingly utilized as writing assistants, highlighting their significant role in educational tools. Gazelle, supports the development of AI-driven tools that facilitate learning and teaching in Arabic writing. Gazelle focuses on a broad spectrum of writing tasks and aims to assist both non-native Arabic learners and native speakers in understanding the pedagogical aspects of Arabic writing. This approach not only bridges the gap between learners and fluent written communication but also enriches the educational tools available for teaching Arabic. By offering comprehensive resources tailored to diverse writing needs, Gazelle enhances the capability of educational platforms to help users master the intricacies of Arabic writing. Data privacy. In relation to the data used in this work, all datasets are publicly available. Therefore, we do not have privacy concerns.

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Appendices

We provide an addition organized as follows:

- Detailed Related Works A.
- Linguistic Background of Arabic B.
- Extended ALC Error Taxonomy D.
- ATB Synthetic Data E.
- Prompt Design F.
- Evaluation matrices for Arabic Writing Assistant Tasks G.

A Detailed Related Works

LLM's for Writing assistance. Advancements in instruction tuning for writing assistance include works like PEER (Schick et al., 2022), which enhances editing by adhering to and explaining a userprovided plan, and CoEdIT (Raheja et al., 2023), which focuses on managing editing plans to refine and clarify content without introducing new information. Additionally, SWIF²T (Chamoun et al., 2024), designed for scientific writing, generates specific, actionable comments to identify weaknesses in a paper and suggest revisions. These developments highlight the progress in creating sophisticated tools that enhance the writing and editing processes across various applications.

Progress in Arabic Writing Tasks. In GEC, advances include the QALB corpus used for the QALB 2014 and 2015 shared tasks (Zaghouani et al., 2014; Rozovskaya et al., 2015), and the Zaebuc corpus (Habash and Palfreyman, 2022). Advances in model techniques include Convolutional Neural Networks, alignment algorithms, LLMs (Solyman et al., 2019, 2021; Alhafni et al., 2023; Kwon et al., 2023). In text simplification, tools such as visualization for assisted text simplification (Hazim et al., 2022) and feature optimization techniques (Saddiki et al., 2018) have been developed, along with corpus advancements like the SAMER corpus (Al Khalil et al., 2018; Alhafni et al., 2024). For text summarization, model developments include survey approaches (Einieh and AlMansour, 2022), rhetorical structure theory with statistical methods (Lagrini and Redjimi, 2021), and deep learning approaches (Al-Maleh and Desouki, 2020).

Explainable Writing Systems. Explainable writing systems enhance the transparency of language processing tools by providing clear and understandable insights aligned with instructional goals. For example, ERRANT (Bryant et al., 2017b) annotates grammatical errors with clear edit boundaries and error types. EXPECT (Fei et al., 2023) offers a dataset with detailed annotations to support explainable grammatical error correction. GEE (Song et al., 2023) advances this by providing one-sentence explanations for grammatical errors in pairs of erroneous and corrected sentences. In text simplification and feedback generation, systems strive to provide clear and relevant explanations (Agarwal, 2022). These efforts highlight the importance of creating tools that deliver understandable insights and ensure alignment with instructional goals. Additionally, understanding the properties and challenges of LLM-generated explanations (Kunz and Kuhlmann, 2024) is crucial for maintaining user trust and comprehension.

B Linguistic Background of Arabic

Arabic is a highly sophisticated and complex language, distinguished by the richness of its morphological and grammatical features (Holes, 2004). It is linguistically diverse, encompassing numerous dialects across a widespread geographical region (Versteegh, 2014). Arabic is recognized as a diglossic language, where both Modern Standard Arabic (MSA) and various dialects coexist (Ferguson, 2020). MSA is employed in formal contexts, whereas local dialects dominate everyday communication, exhibiting significant differences in pronunciation, vocabulary, and grammar. The inherent complexity and diversity of Arabic presents considerable challenges in the field of NLP, making efforts in writing tasks and writing assistance valuable. For instance, Arabic verbs are intricate, changing based on tense, mood, voice, and gender, posing significant challenges for writing tasks. Moreover, the grammar includes complex rules, such as changes in noun forms depending on their grammatical role. Additionally, Arabic is orthographically ambiguous due to its reliance on consonants and the optional use of diacritics to denote short vowels and other phonetic details (Sawalha et al., 2013). This ambiguity leads to multiple interpretations of the same consonant string without context or diacritics, complicating writing in Arabic (Abdul-Mageed et al., 2020; Belkebir and

Habash, 2021a). For example, the word علم with diacritics has three different meanings: علمَ meaning (he knew), علَم يَتُم meaning (knowledge), and علَم meaning (flag).

Furthermore, the morphological ambiguity of Arabic occurs when the same root or pattern leads to different meanings based on context, inflection, or derivation. Arabic's rich system of roots and patterns (templates) allows for a single root to generate various words with different meanings and grammatical roles. The root of the verb <u>ضربب</u> (hit), for instance, has different patterns indicating tense, voice (active/passive), and other grammatical nuances, such as <u>different</u> be hit) vs. <u>y</u> (yuárib - he is hitting).

C Writing Assistance Instructions

GEC Instructions. For example, the Orthographic error class features a subclass for *hamza* errors, further divided into four sub-subclasses: *medial hamza, final hamza, cutting hamza,* and *hamzet al-wasl.* Our instructions address a broad spectrum of these sub-classes and sub-subclasses, ensuring comprehensive coverage across different error categories.

GEC Error Explanations. In our dataset, we provide explanation of the GEC errors in both Arabic and English. For instance, consider the sentence information instance, consider the sentence (goes against human rights), which contains a *Syntax* error. The English explanation is: Adding the definite article *u* to the annexed noun is incorrect because the annexed noun and the annexing noun should share the same definiteness or indefiniteness. In another example, *marc i*tedic *i*tedic *i*tedic. In another example, *marc i*tedic *i*tedic *i*tedic. In another example, *marc i*tedic *i*tedic *i*tedic *i*tedic *i*tedic explanation is: *Orthographic* error, the Arabic explanation is: *i*tedic *i*

ATB Synthetic Data. We utilize all parts of the ATB to generate 100 examples related to different classes of errors in our taxonomy, covering the following error classes and sub-classes:

• Orthographic errors, including:

i) Wrong Order of Word Characters (OC), ii) Replacement in Word Characters (OR), iii) Additional Characters (OD), iv) Missing Characters (OM). • Syntax errors, which include:

i) Missing Words (XM), ii) Unnecessary Words (XT).

- Morphological errors, involving: i) Word Inflection (MI), ii) Verb Tense (MT).
- Split and Merge
- Punctuation errors, categorized into:

i) Punctuation Confusion (PC), ii) Missing Punctuation (PM), iii) Unnecessary Punctuation (PT), iv) Other Punctuation Errors (PO).

Text Refinement

For instance, the informal use of the following expression in MSA: نعم، يا سعد بيه، ليس فيها أي خدوش، يسعد بيه، ليس فيها أي خدوش، would be polished to be: نعم، يا سيد سعد، ليس فيها أي خدوش، The explanation provided is: The word موجودة، وتممت عليها في مخازن الشركة. The explanation provided is: The word موجودة، وتممت عليها في مخازن الشركة. dard Arabic, so it was necessary to phrase it as . Another example of text refinement is جائسن ترغون أمت ما زئتم ما زئتم so it is: The explanation provided is: The correct explanation provided. an incorrect word and does not exist in Standard Arabic; the correct equivalent is . .

D Extended ALC Error Taxonomy

Orthographic Errors refer to mistakes in the spelling of a word. It occurs when the arrangement of letters does not match the standard or accepted spelling. These errors can happen for several reasons, such as typing mistakes, incorrect memory of the spelling, or unfamiliarity with the spelling rules of a language. Orthographic errors are particularly common in languages with complex and irregular spelling rules, like Arabic. For instance, there are common spelling errors in medial hamza as in راى instead of راى. Other error examples include the confusion between Ta mabsouta and Ta marbouta as in instead of طارت. Within the Orthographic errors category, which originally encompasses 12 subclasses as per the ALC framework, we have introduced additional granularity by defining further sub-subclasses. These include four distinct categories for Hamza errors: i) Medial hamza, ii) Final hamza, iii) Cutting hamza, and iv) Hamzat

al-wasl. Additionally, we address the common confusions between Ha, Ta, and Ta marbouta by subdividing them into i) *Ta mabsouta*, ii) *Ta marbouta*, and iii) *Ha*.

Syntax Errors in language use refer to errors in the structure of a sentence which include the arrangement of words and phrases in ways that do not conform to the grammatical rules of the language, making the sentence unclear or incorrect. Syntax errors can involve incorrect word order, missing components like subjects or verbs, or improper use of grammatical forms such as agreement, or conjugation. In Arabic, errors include the gender, number, cases, etc. For the error in dual أطلق الجنديد رصاصتان, example in Arabic. صاصتيد which should be رصاصتان For the Syntax error category, which initially comprised seven subclasses, we have introduced an additional subclass titled Closed class errors. Further, the gender error subclass is now refined into a sub-subclass errors of using feminine and masculine forms and vice versa. The number subclass has been divided into four sub-subclasses: i) singular, ii) dual, iii) plural, and iv) numbers with additional subdivisions under plural-namely i) sound masculine plural, ii) sound feminine plural, iii) broken plural, and iv) Al-maqsour plural. Additionally, we have structured the number into three further sub-subclasses: i) singular numbers, ii) composite numbers, and iii) Al-Aqoud.

We further refined the taxonomy by introducing two sub-subclasses under definiteness, specifically addition and omission of the definite article "Al." Additionally, we have delineated five sub-subclasses within the category of case errors: i) nominative, ii) genitive, iii) accusative, iv) jussive, v) and other case errors. We also introduced a new subclass titled Closed class category. This category captures miscellaneous grammatical inaccuracies involving i) pronouns, ii) the five verbs, and iii) the five nouns that do not fit neatly into other predefined categories. The pronouns sub-subclass is divided into three specific issues: i) adding unnecessary pronoun, ii) removing necessary pronoun, iii) and wrong pronoun reference.

Semantic Errors refer to an error in the meaning or interpretation of a sentence or phrase, despite it being grammatically correct. This type

of error occurs when words or phrases are used inappropriately, leading to confusion or a failure to convey the intended message. Semantic errors can stem from using a word that does not have the intended meaning of the sentence, or from a logical inconsistency in the statement. For instance, adding unnecessary conjunction as قرزات the error here lies in the ، الكتاب والذى كان مفيداً extra conjunction واو in the sentence. Also, there is an error of missing the preposition محو لة in إلى In the semantics category, المنازل ثكنات عسكرية which initially comprised three subclasses, we added a new subclass designated Special Expressions. This subclass addresses the incorrect usage of special expressions at either the word or phrase level. Breakdown of this category includes a Word Selection Error subclass divided into five further categories: i) Adding unnecessary preposition, ii) Removing necessary preposition, iii) Replacing preposition, iv) Preposition use, v) and other word selection errors. Additionally, for conjunction errors, we organized this into four sub-subclasses: i) Adding unnecessary conjunction, ii) Removing necessary conjunction, iii) Replacing conjunction, iv) and other Atf errors. The subsubclasses we introduced in the semantic errors might appear to overlap with the missing and additional characters in the syntax class, but the errors we generated impact the sentence's semantic meaning rather than its structural integrity.

Punctuation Errors occur when punctuation marks are misused, omitted, or placed incorrectly within sentences. These errors can alter the clarity, flow, and meaning of text. Typical punctuation errors include the misuse of commas, periods, semicolons, colons, and quotation marks, etc. For instance, the confusion of using question mark in instead of using the exclamation ما أروع القمر؟ mark ! ما أروع القمر. Within the framework of the original error taxonomy, punctuation errors are categorized into four subclasses: i) missing punctuation, ii) punctuation confusion, iii) unnecessary punctuation, iv) and other punctuation errors. These subclasses are further divided into detailed sub subclasses that specifically address various punctuation marks, such as commas, exclamation marks, and full stops, etc.

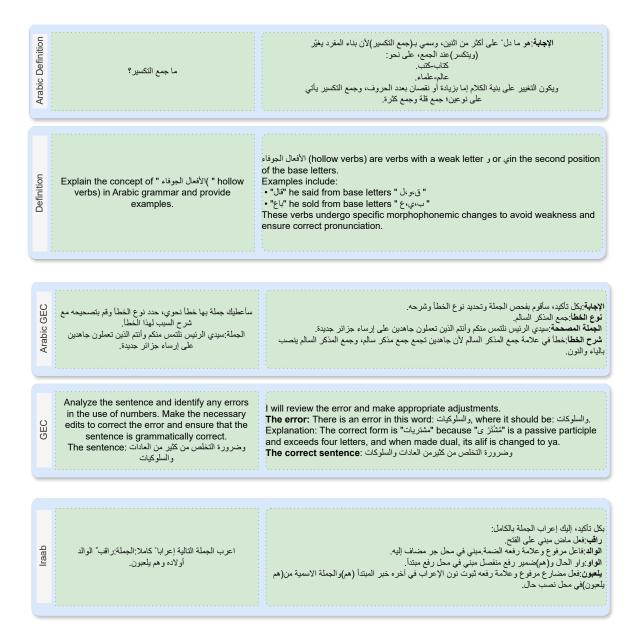


Figure D.1: Examples of writing assistance instructions in Arabic and English.

	Tag	Subclass	Sub2	Sub3	Description	Exam
			Medial Hamza	_	Medial Hamza E.	تاءب ← ڪتائب
	OH		Final Hamza	_	Final Hamza E.	طو ← تباطؤ
		Hamza	Cutting Hamzah	_	Cutting Hamzah E.	همت ← أسهمت
			Hamzet al-Wasl	_	Hamzet al Wasel E.	تعلمت ← استعلمت
	OA	C. in Alif Ya and Alif-Maqsura	Shortening Alif/ Alif Maqsoura	_	C. in Alif Ya, and Alif-Maqsura	ىتوي ← مستوى
	OW	C. in Alif Fariqa		_	C. in Alif Fariqa	ہُوا ← سمُو
			Ta Mabsouta	_	C. in Ta Mabsouta	رة → طارت
	OT	C. in Ha, Ta and Ta-Marbuta	Ta Marbouta	_	C. in Ta Marbouta	رة ← اتنزه
			На	_	C. in Ha	رد تابة → ڪتابه
hy	ON	C. between Nun and Tanwin	_	_	C. between Nun and Tanwin	ابرن ← مثابرٌ
rap	os	Shortening long vowels	_	_	Shortening long vowels	.دون کر تھم ← ذاکر تھم
Orthography	OG	Lengthening short vowels	_	_	Lengthening short vowels	-ریها > 1-ریها کذا ← هکذا
P	OC		_	_	Wrong order of word Chr.(s)	
	OR	Wrong order of word Chr.(s)	_			یمب ← بکم
		Replacement in Word Chr.(s)		_	Rep. in word Chr.(s)	وبل ← تحويل
	OD	Additional Chr.(s)	_	_	Adding unnecessary Chr.(s)	سم ← اسم
	OM	Missing Chr.(s)	_	_	Missing necessary Chr.(s)	ال ← قنابل
	00	Other Orthographic E.	-	_	Other orthographic E.	
			Fem. Vs. Masc.	—	C. in Fem. Vs. Masc.	رب ← تشرب
	XG	Gender	Singular	_	C. in Sing. Vs. Pl.	لحل ← النحلة
			Dual	-	C. in Dual	معلمين - المعلمان
				Sound Masc. Pl.	Wrong Sound Masc. Pl.	دب ← مؤدبون
				Broken Pl.	Wrong Broken Pl.	دیدین ← سعداء
			Plural	Almaqsour Pl.	Wrong AlMaqsour Pl.	۔ ۔ ۔ مشتروات ← المشتريات
				Sound Fem. Pl.	Wrong Sound Fem. Pl.	
	XN	Number				تبوا ← ڪتبن
				Sing. Num.	C. in Sing. Num.	ذِتْ أيام ← ثلاثة أيام
			Numbers	Composite Num.	C. in Composite Num.	بع عشر مبدعا ← أربعة عشر
				Al-Aqoud	C. in Al-Aqoud	فمسون ← الخمسين
	VE	Defeitence	Adding "Al"	_	Adding "Al"	ىنتصف ← منتصف
	XF	Definiteness	Removing "Al"	_	C. in Removing Al	لمي ← العالمي
			Nom. Case E.	_	C. in Nom. Case	مرضين - الممرضون
			Gen. Case E.	_	C. in Gen. Case	ی عرفاتاً ← عرفاتٌ
			Acc. Case E.		C. in Acc. Case	
tax	XC	Case		_		دي ← عاديا
Syntax			Juss. Case E.	_	C. in Juss. Case	عوا ← يدء
•,			Other Case E.	_	Other Case E.	-
				Adding Unnecessary Pron.	C. in Adding Pron.	ر ایته ← ر ایت
			Pronouns	Removing Necessary Pron.	C. in Removing Pron.	د ← أخذنا
	VD	Closed Class E.		Wrong Pron. Ref.	C. in Pron. Ref.	از لهم ← مناز لهن
	XR	Closed Class E.	The Five N.	_	C. in Five N.	رك → أبيك
			The Five V.	_	C. in Five V.	نعی ← تقنعین
	XM	Missing Word	_	_	Missing Certain word	تضيف ← ان تستضيف
				_	Adding Unnecessary Word	الحالة ← الحالة
	XT	Unnecessary Word				
	XT XO	Unnecessary Word Other Syntactic E	_	_	Other Syntactic E	
	XT XO	Unnecessary Word Other Syntactic E.	_	_	Other Syntactic E.	
			Removing Necessary Prep.	-	C. in Removing Necessary Prep.	بيع ← للربيع
				- - -	C. in Removing Necessary Prep. C. in Replacing Prep.	۔بیع ← ٹلربیع ، سیار تنا ← بسیار تنا
			Removing Necessary Prep.		C. in Removing Necessary Prep.	.بیع ← ٹلربیع , سیار تنا ← بسیار تنا
					C. in Removing Necessary Prep. C. in Replacing Prep.	.بیع ← ٹلربیع , سیار تنا ← بسیار تنا
	XO	Other Syntactic E.	Removing Necessary Prep. Replacing Prep. Adding Unnecessary Prep.	_	C. in Removing Necessary Prep. C. in Replacing Prep.	بیع ← للربیع ، سیارتنا ← بسیارتنا زوراء ← وراء
	XO	Other Syntactic E.	Removing Necessary Prep. Replacing Prep. Adding Unnecessary Prep. Other Preposition E.	_	C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep.	بیع ← للربیع ، سیارتنا ← بسیارتنا ، وراء ← وراء
S	XO	Other Syntactic E.	Removing Necessary Prep. Replacing Prep. Adding Unnecessary Prep. Other Preposition E. Preposition Use Other Word Selection E.	- - -	C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Prep. Use C. in Other Word Selection E.	ربیع ← ٹلر بیع ہ سیار تنا ← بسیار تنا ز وراء ← وراء سطریقة ← طریقة
antics	XO	Other Syntactic E.	Removing Necessary Prep. Replacing Prep. Adding Unnecessary Prep. Other Preposition E. Preposition Use Other Word Selection E. Adding Unnecessary Conj.		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Prep. Use C. in Other Word Selection E. C. in Adding Unnecessary Conj.	ربيع ← للربيع سيار تنا ← بسيار تنا ز وراء ← وراء طريقة ← طريقة تي إلى ← إلى
emantics	XO SW	Other Syntactic E.	Removing Necessary Prep. Replacing Prep. Adding Unnecessary Prep. Other Preposition E. Preposition Use Other Word Selection E. Adding Unnecessary Conj. Removing Necessary Conj.		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Prep. Use C. in Other Word Selection E. C. in Adding Unnecessary Conj. C. in Removing Necessary Conjunction	ربيع ← للربيع ، سيار تنا ← بسيار تنا ز وراء ← وراء سطريقة ← طريقة تى إلى ← إلى سير، الموظفون ← المدير والموظفون
Semantics	XO	Other Syntactic E.	Removing Necessary Prep. Replacing Prep. Adding Unnccessary Prep. Other Preposition E. Preposition Use Other Word Selection E. Adding Unnecessary Conj. Removing Necessary Conj. Replacing Conj.		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Prep. Use C. in Other Word Selection E. C. in Adding Unnecessary Conj. C. in Removing Necessary Conjunction C. in Replacing Conj.	ربيع ← للربيع ي سيار تنا ← بسيار تنا ز وراء ← وراء سطريقة ← طريقة تي إلى ← إلى دير، الموظفون ← المدير والموظفون مجتمع ← والمجتمع
Semantics	XO SW SF	Other Syntactic E. Word Selection E. Conjunction E.	Removing Necessary Prep. Replacing Prep. Adding Unnccessary Prep. Other Preposition E. Preposition Use Other Word Selection E. Adding Unnecessary Conj. Removing Necessary Conj. Replacing Conj. Other Arf E.		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Prep. Use C. in Other Word Selection E. C. in Adding Unnecessary Conj. C. in Removing Necessary Conjunction C. in Replacing Conj. C. in Other Atf E.	بيع ← للربيع ، سيارتنا ← بسيارتنا ، وراء ← وراء طريقة ← طريقة ني إلى ← إلى دير، الموظفون ← المدير والموظفون مجتمع ← والمجتمع مديره ← ومديره
Semantics	XO SW SF SS	Other Syntactic E. Word Selection E. Conjunction E. Special Expression	Removing Necessary Prep. Replacing Prep. Adding Unnccessary Prep. Other Preposition E. Preposition Use Other Word Selection E. Adding Unnecessary Conj. Removing Necessary Conj. Replacing Conj. Other Arf E.		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Prep. Use C. in Other Word Selection E. C. in Adding Unnecessary Conj. C. in Removing Necessary Conjunction C. in Replacing Conj. C. in Other Atf E. C. in Special Expression	.بيع ← للربيع ، سيارتنا ← بسيارتنا ن وراء ← وراء صلريقة ← طريقة ني إلى ← إلى دير، الموظفون ← المدير والموظفون مجتمع ← والمجتمع مديره ← ومديره
Semantics	XO SW SF SS SO	Other Syntactic E. Word Selection E. Conjunction E. Special Expression Other Semantic E.	Removing Necessary Prep. Replacing Prep. Adding Unnccessary Prep. Other Preposition E. Preposition Use Other Word Selection E. Adding Unnecessary Conj. Removing Necessary Conj. Replacing Conj. Other Arf E.		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Prep. Use C. in Other Word Selection E. C. in Adding Unnecessary Conj. C. in Replacing Conj. C. in Replacing Conj. C. in Special Expression Other Semantic E.	بيع ← للربيع ، سيارتنا ← بسيارتنا ، وراء ← وراء طريقة ← طريقة ني إلى ← إلى دير، الموظفون ← المدير والموظفون مجتمع ← والمجتمع مديره ← ومديره
	XO SW SF SS	Other Syntactic E. Word Selection E. Conjunction E. Special Expression	Removing Necessary Prep. Replacing Prep. Adding Unnccessary Prep. Other Preposition E. Preposition Use Other Word Selection E. Adding Unnecessary Conj. Removing Necessary Conj. Replacing Conj. Other Arf E.		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Prep. Use C. in Other Word Selection E. C. in Adding Unnecessary Conj. C. in Removing Necessary Conjunction C. in Replacing Conj. C. in Other Atf E. C. in Special Expression	بيع ← للربيع ، سيارتنا ← بسيارتنا ، وراء ← وراء طريقة ← طريقة ني إلى ← إلى دير، الموظفون ← المدير والموظفون مجتمع ← والمجتمع مديره ← ومديره م مهمة
	XO SW SF SS SO	Other Syntactic E. Word Selection E. Conjunction E. Special Expression Other Semantic E.	Removing Necessary Prep. Replacing Prep. Adding Unnecessary Prep. Other Preposition E. Preposition Use Other Word Selection E. Adding Unnecessary Conj. Removing Necessary Conj. Replacing Conj. Other Arf E.		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Prep. Use C. in Other Word Selection E. C. in Adding Unnecessary Conj. C. in Replacing Conj. C. in Replacing Conj. C. in Special Expression Other Semantic E.	بيع ← للربيع ، سيارتنا ← بسيارتنا ، وراء ← وراء طريقة ← طريقة ني إلى ← إلى دير، الموظفون ← المدير والموظفون دير، الموظفون ← المدير والموظفون مديره ← ومديره نية ← شمائنة
	XO SW SF SS SO MI	Other Syntactic E. Word Selection E. Conjunction E. Special Expression Other Semantic E. Word Inflection	Removing Necessary Prep. Replacing Prep. Adding Unnecessary Prep. Other Preposition E. Preposition Use Other Word Selection E. Adding Unnecessary Conj. Removing Necessary Conj. Replacing Conj. Other Atf E.		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Prep. Use C. in Other Word Selection E. C. in Adding Unnecessary Conjunction C. in Removing Necessary Conjunction C. in Replacing Conj. C. in Other Aff E. C. in Special Expression Other Semantic E. C. in Word Inflection	بيع ← للربيع ، سيارتنا ← بسيارتنا ، وراء ← وراء طريقة ← طريقة ني إلى ← إلى دير، الموظفون ← المدير والموظفون دير، الموظفون ← المدير والموظفون مديره ← ومديره نية ← شمائنة
	XO SW SF SS SO MI MT	Other Syntactic E. Word Selection E. Conjunction E. Special Expression Other Semantic E. Word Inflection Verb Tense	Removing Necessary Prep. Replacing Prep. Adding Unnecessary Prep. Other Preposition E. Preposition Use Other Word Selection E. Adding Unnecessary Conj. Removing Necessary Conj. Replacing Conj. Other Atf E.		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Other Word Selection E. C. in Other Word Selection E. C. in Adding Unnecessary Conj. C. in Removing Necessary Conjunction C. in Replacing Conj. C. in Other Art E. C. in Other Art E. C. in Special Expression Other Semantic E. C. in Word Inflection C. in Verb Tense Other Morphological E. E. in Exclamation Marks.	بيع → للربيع سيارتنا ← بسيارتنا ، وراء ← وراء طريقة ← طريقة ني إلى ← إلى نير، الموظفون ← المدير والموظفون نير، الموظفون ← المدير والموظفون مديرد ← ومديرد مديرد ← ميمة ينة ← شائنة ش ← عاش
	XO SW SF SS SO MI MT	Other Syntactic E. Word Selection E. Conjunction E. Special Expression Other Semantic E. Word Inflection Verb Tense	Exclamation Mark (!)		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Other Word Selection E. C. in Other Word Selection E. C. in Adding Unnecessary Conjunction C. in Replacing Conj. C. in Replacing Conj. C. in Oper Arf E. C. in Special Expression Other Arf E. C. in Word Inflection C. in Verb Tense Other Morphological E. E. in Exclamation Marks. E. in Semicolon.	بيع ← للربيع ، سيارتنا ← بسيارتنا ، وراء ← وراء طريقة ← طريقة مي الى ← الى دير، الموظفون ← المدير والموظفون دير، الموظفون ← المدير والموظفون مديره ← و مديره مديره ← و مديره ش ← عاش ش ← عاش اجمل؟ ← ما اجمل!
Morph	XO SW SF SS SO MI MT	Other Syntactic E. Word Selection E. Conjunction E. Special Expression Other Semantic E. Word Inflection Verb Tense	Exclamation Mark (!) Semicolon (;)		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Other Word Selection E. C. in Other Word Selection E. C. in Other Word Selection E. C. in Adding Unnecessary Conjunction C. in Removing Necessary Conjunction C. in Replacing Conj. C. in Other Art F. C. in Special Expression Other Semantic E. C. in Word Inflection C. in Verb Tense Other Morphological E. E. in Exclamation Marks. E. in Semicolon. E. in Colon.	يبع ← للربيع ، سيارتنا ← بسيارتنا ، وراء ← وراء طريقة ← طريقة نی إلی ← إلی نی الموظفون ← المدير والموظفون مديره ← ومديره مديره ← ومديره مديره ← مديره ش ← عاش ش ← عاش اجمل۶ ← ما أجمل! ل العلم: → قال الحملم:
Morph	XO SW SF SS SO MI MT MO	Other Syntactic E. Word Selection E. Conjunction E. Special Expression Other Semantic E. Word Inflection Verb Tense Other Morphological E. Punctuation C.	Exclamation Mark (!) Semicolon (.) Colon		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Other Word Selection E. C. in Other Word Selection E. C. in Other Word Selection E. C. in Adding Unnecessary Conj. C. in Removing Necessary Conjunction C. in Replacing Conj. C. in Other Atf E. C. in Special Expression Other Semantic E. C. in Word Inflection C. in Verb Tense Other Morphological E. E. in Exclamation Marks. E. in Semicolon. E. in Colon. E. in Clon.	بيع → للربيع سيارتنا → بسيارتنا ، وراء → وراء طريقة → طريقة ميرير، الموظفون → المدير والموظفون .ير، الموظفون → المدير والموظفون مدير د → ومديره مدير د → ومديره منية → ميانة ش → عاش ش → عاش ي العليي: → قدال العلمي: المعلم: → قال العملم:
Morph	XO SW SF SS SO MI MT MO	Other Syntactic E. Word Selection E. Conjunction E. Special Expression Other Semantic E. Word Inflection Verb Tense Other Morphological E. Punctuation C. Missing Punctuation			C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Other Word Selection E. C. in Other Word Selection E. C. in Other Word Selection E. C. in Adding Unnecessary Conjunction C. in Removing Necessary Conjunction C. in Replacing Conj. C. in Other Art F. C. in Special Expression Other Semantic E. C. in Word Inflection C. in Verb Tense Other Morphological E. E. in Exclamation Marks. E. in Semicolon. E. in Colon.	بيع → للربيع سيارتنا → بسيارتنا ، وراء → وراء طريقة → طريقة ماريقة → طريقة -ير، الموظفون → المدير والموظفون -ير، الموظفون → المدير والموظفون مديره → ومديره مديره → ومديره ت ماينه ماينه → ماينة ش → عاش ش → عاش ي المعلم: → قال العيم. وا احدهما → فيقول احدهما.
Morph	XO SW SF SS SO MI MT MO PC PM PT	Other Syntactic E. Word Selection E. Conjunction E. Special Expression Other Semantic E. Word Inflection Verb Tense Other Morphological E. Punctuation C. Missing Punctuation Unnecessary Punctuation	— Removing Necessary Prep. Replacing Prep. Adding Unnecessary Prep. Other Preposition E. Preposition Use Other Word Selection E. Adding Unnecessary Conj. Removing Necessary Conj. Replacing Conj. Other Arf E. — — — Exclamation Mark (1) Semicolon (:) Colon (:) Ellipsis () Quotations Marks (" ") Square Brackets [] Comma (.)		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Other Word Selection E. C. in Other Word Selection E. C. in Adding Unnecessary Conj. C. in Removing Necessary Conjunction C. in Replacing Conj. C. in Other Atf E. C. in Special Expression Other Semantic E. C. in Word Inflection C. in Verb Tense Other Morphological E. E. in Exclamation Marks. E. in Semicolon. E. in Colon. E. in Colon. E. in Colon. E. in Guotation Marks. E. in Square Brackets. E. in Square Brackets. E. in Square Brackets.	$\begin{split} \begin{array}{l} + + + + + + + + + + + + + + + + + + +$
Morph	XO SW SF SS SO MI MT MO	Other Syntactic E. Word Selection E. Conjunction E. Special Expression Other Semantic E. Word Inflection Verb Tense Other Morphological E. Punctuation C. Missing Punctuation	— Removing Necessary Prep. Replacing Prep. Adding Unnecessary Prep. Other Preposition E. Preposition Use Other Word Selection E. Adding Unnecessary Conj. Removing Necessary Conj. Replacing Conj. Other Arf E. Exclamation Mark (!) Semicolon (.) Colon (.) Colon (.) Colon (.) Square Brackets [] Comma (.) Question Mark (?)		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Other Word Selection E. C. in Other Word Selection E. C. in Adding Unnecessary Conjunction C. in Removing Necessary Conjunction C. in Replacing Conj. C. in Other Aff E. C. in Other Aff E. C. in Special Expression Other Semantic E. C. in Word Inflection C. in Verb Tense Other Morphological E. E. in Exclamation Marks. E. in Sequestion. E. in Colon. E. in Colon. E. in Guation Marks. E. in Square Brackets. E. in Square Brackets. E. in Comma. E. in Comma.	بيع → للربيع سيار تنا ← بسيار تنا ، وراء ← وراء طريقة ← طريقة حير، الموظفون ← المدير والموظفون -ير، الموظفون ← المدير والموظفون مدير د ← ومدير د مدير د ← ومدير د مدير د ← ومدير د منيز - مائنة ش ← عاش ش ← عاش ول احدما. ← فيقول احدما. ول احدما. ← فيقول احدما. مر، ← الشعر يف ذميت. ← كيف ذميت؟
Morph	XO SW SF SS SO MI MT MO PC PM PT	Other Syntactic E. Word Selection E. Conjunction E. Special Expression Other Semantic E. Word Inflection Verb Tense Other Morphological E. Punctuation C. Missing Punctuation Unnecessary Punctuation	— Removing Necessary Prep. Replacing Prep. Adding Unnecessary Prep. Other Preposition E. Preposition Use Other Word Selection E. Adding Unnecessary Conj. Replacing Conj. Other Aft E. — — — Exclamation Mark (!) Semicolon (.) Colino (.) Colino (.) Colino (.) Colino (.) Quotations Marks (* ") Square Brackets [] Comma (.) Question Mark (?) Parenthesis (.)		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Other Word Selection E. C. in Other Word Selection E. C. in Other Word Selection E. C. in Adding Unnecessary Conj. C. in Removing Necessary Conjunction C. in Replacing Conj. C. in Other Artf E. C. in Special Expression Other Semantic E. C. in Word Inflection C. in Word Inflection C. in Verb Tense Other Morphological E. E. in Exclamation Marks. E. in Semicolon. E. in Ellipsis. E. in Quotation Marks. E. in Square Brackets. E. in Comma. E. in Comma. E. in Comma. E. in Comma. E. in Comma. E. in Partice Section Marks.	$\begin{split} \begin{array}{c} + + + + + + + + + + + + + + + + + + +$
Morph	XO SW SF SS SO MI MT MO PC PM PT	Other Syntactic E. Word Selection E. Conjunction E. Special Expression Other Semantic E. Word Inflection Verb Tense Other Morphological E. Punctuation C. Missing Punctuation Unnecessary Punctuation	— Removing Necessary Prep. Replacing Prep. Adding Unnecessary Prep. Other Preposition E. Preposition Use Other Word Selection E. Adding Unnecessary Conj. Removing Necessary Conj. Removing Necessary Conj. Other Arf E. Exclamation Mark (1) Semicolon (2) Colon (2) Colon (2) Cultions Marks (1***) Square Brackets [] Corma (2) Question Mark (2) Parenthesis (1) Dash (-2)		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Other Word Selection E. C. in Other Word Selection E. C. in Adding Unnecessary Conj. C. in Replacing Conj. C. in Replacing Conj. C. in Other Aff E. C. in Other Aff E. C. in Special Expression Other Semantic E. C. in Word Inflection C. in Verb Tense Other Morphological E. E. in Exclamation Marks. E. in Semicolon. E. in Colon. E. in Colon. E. in Colon. E. in Colon. E. in Square Brackets. E. in Square Brackets. E. in Square Brackets. E. in Colon Marks. E. in Colon. E. in Inter Marks. E. in Square Brackets. E. in Colon. E. in Colon. E. in Colon. E. in the Question Marks. E. in Parenthesis. E. in Dash.	. بيع → للربيع . سيارتنا ← بسيارتنا ن وراء ← وراء ن وراء ← وراء صلريقة ← طريقة تى إلى ← إلى دير. الموظفون ← المدير والموظفون محتمع ← والمجتمع مديره ← ومديره مديره ← ومديره ش ← عاش ش ← عاش ش ← عاش بت إلى الطبيب: ← ذهبت إلى الطبيب ال المعلم: ← فال المعلم: نول احدهما. ← فيقول احدهما. نول احدهما. ← كيف ذهبت؟ مر ← نعم نفر (من ← مؤلفة من ن الفرادها ← بعض أفرادها
Punctuation Morph Semantics	XO SW SF SS SO MI MT MO PC PM PT	Other Syntactic E. Word Selection E. Conjunction E. Special Expression Other Semantic E. Word Inflection Verb Tense Other Morphological E. Punctuation C. Missing Punctuation Unnecessary Punctuation	— Removing Necessary Prep. Replacing Prep. Adding Unnecessary Prep. Other Preposition E. Preposition Use Other Word Selection E. Adding Unnecessary Conj. Replacing Conj. Other Art E. — — — Exclamation Mark (!) Semicolon (;) Colino (;) Colino (;) Colino (;) Colino (;) Colino (;) Quotations Marks (* ") Square Brackets [] Comma (,) Question Mark (?) Parenthesis ()		C. in Removing Necessary Prep. C. in Replacing Prep. C. in Adding Unnecessary Prep. C. in Other Word Selection E. C. in Other Word Selection E. C. in Other Word Selection E. C. in Adding Unnecessary Conj. C. in Removing Necessary Conjunction C. in Replacing Conj. C. in Other Artf E. C. in Special Expression Other Semantic E. C. in Word Inflection C. in Word Inflection C. in Verb Tense Other Morphological E. E. in Exclamation Marks. E. in Semicolon. E. in Ellipsis. E. in Quotation Marks. E. in Square Brackets. E. in Comma. E. in Comma. E. in Comma. E. in Comma. E. in Comma. E. in Partice Section Marks.	ربيع ← للربيع ، سيار تنا ← بسيار تنا ز وراء ← وراء سطريقة ← طريقة تى إلى ← إلى سير، الموظفون ← المدير والموظفون

Table D.1: The ALC error taxonomy has been expanded with new subcategories and subdivisions. Error tags are listed alphabetically, except for the 'Other' tags, which are excluded in this extension. **The table includes abbreviations:** *Chr. for 'Characters' *Fem for 'Feminine' *Masc. for 'Masculine' *Sing. for 'Singular' *P1. for 'Plural' *Num. for 'Number' *Conj. for 'Conjunctions' *Nom. for 'Nominative' *Juss. for 'Jussive' *Pron. for 'Pronouns' *Acc. for 'Accusative' *C for 'Confusion' and *E for 'Error(s). **Morph:** Morphology, Class: Error Class, Tag: Error Tag, Sub2: Subclass of a subclass of a subclass of a subclass.

Morphological Template	Description
Template 1: فعل (fa'ala)	Expresses the general verbal meaning of the root in question.
Template 2: فعّل (fa"al)	Built on template 1 by doubling the middle radical (adding a shadda to it). Often is an intensive or causative version of template 1.
Template 3: فاعل (faa'il)	Built on template 1 by adding an alif between the first and second radicals. It gives an transitive or indicates a relation meaning to the form 1 verb, describes someone doing the act to or with someone else.
Template 4: أفعل (af'al)	Built on template 1 by prefixing an alif and putting a sukuun over the first radical. Similar to template 2 in that it is usually a causative or transitive version of template 1.
(taff'al) تفعّل :Template 5	Built on template 2 by adding the prefix <u></u> (ta). Often a reflexive or passive version of template 2.
Template 6: تفاعل (tafaa'al)	Built on template 3 by adding the prefix ـــ (ta). Usually a reflex- ive or passive version of template 3.
Template 7: انفعل (infa'ala)	Built on template 1 by adding the prefix نفر (inna). Usually a re- flexive and/or passive version of template 1.
Template 8: افتعل (ifta'la)	Built on template 1 by adding the prefix 1 (?a) and placing a sukuun must be placed over its first radical.It indicate a reflexive nuances or doing something intentionally version of the template 1.
Template 9: افعدً (if'all)	Built on template 1 by adding the prefix (?a), placing a sukuun over its first radical, and adding a shadda to the last radical.
istf'al) استفعل (istf'al)	Built on template 1 by adding the prefix است (?sta) and inserting a (ta) between the first and second radicals, a sukuun must be placed over the first radical. Often a considerative version of template 1, means to consider or to deem someone in relation to template 1.

Table D.2: Synthetic error generation templates for word inflection based on the ATB.

E ATB Synthetic Data

Orthographic Errors

Missing Characters (OM) In generating OM errors, we apply three distinct types of rules. The initial approach involves randomly removing a character, with each character having an equal probability of being removed, or following a distribution where certain characters like م, ع, ف, are more likely to be removed than others. The second rule focuses on removing a character in instances of repetition. For example: عملية would be جيا would be جيا be example.

• Wrong Order of Word Characters (OC) When generating OC errors, we either shuffle two adjacent characters within the same word or find a word that shares the same characters as the target word aimed to change and has a Levenshtein distance of 2. For example يجب would be جيب

- Replacement in word characters (OR) In generating OR errors, we pursue two distinct methods. The first one, we seek a word with a Levenshtein distance of 1 from the target word. For the second one, we randomly select a character and replace it with another character based on specific criteria: 1- Characters that are visually similar in shape, 2-Characters that are located near each other on the keyboard, 3- Characters that have similar sounds or are phonetically close when pronounced. For example, if we change the character i, we might select i, j, or i as alternatives. For the character ط, possible substitutions include د , ص , ض , ص ,ظ , ت For instance, the word البر تقال could be altered to البر تغال. is replaced with ¿, as they ق is replaced with are similar in shape and located close to each other on the keyboard.
- Missing Characters (OM)) In generating OM errors, we follow three distinct techniques. The first technique involves adding

characters that are pronounced but should not be written. For instance, in the case of Alif al mad التنوين and Tanwin التنوين, the Alif is pronounced in the word هدا , but it should not be written. Thus, the resulting error word is هاذا. The second one involves randomly adding characters. For example, the word ففي could be altered to في. The third technique requires searching for a word that has a Levenshtein distance of 1 from the target word and is shorter in length. For example, as could be changed to a.

Syntax Errors

- Missing Word (XM) In generating XM errors, we employ the following strategies: 1-remove pronouns such as such as demonstrative, reflexive pronouns, ... etc. 2-remove conjunctions, prepositions, or inna المنابع 3-remove bi-gram collocation words. For instance في would be altered to الدور would be altered to الدور.
- Unnecessary Word (XT) In XT error generation, we employ the following strategies:
 1- Add conjunctions and prepositions. 2- Include unnecessary pronouns. For example, in the phrase نلعب نحن, the pronoun نلعب is redundant since it is already indicated by the i in the verb لعب 3- Add bi-gram collocation words. For instance, علي could be modified to ما يحدث يطبع b.

Morphological Errors

• In Morphological errors, there are two types of error generated: word inflection and verb tense. Starting with word inflection, in the Arabic language most of the words are derived from three literal root which represents a core meaning or concept. There are cases for four, and five literal root, but the most common one is three literal root. By using the root, a variety of nouns, verbs, adjectives, active participles, and passive participles could be derived by adding specific prefixes, suffixes and using special templates. Each template has a basic meaning associated with the general meaning of the root being used. To derive word inflection errors, we transform any noun, verb, or adjective to another one by changing its template while preserving its meaning by checking the gloss of the original

word and generated inflection. We have used the certain templates to derive inflection on words.For example, An example of inflection would be المشهورة. Table D.2 shows the employed templates.

• In Arabic verb tense errors, verbs are modified using specific suffixes and prefixes to indicate gender, number, and person. To transform one verb tense to another, these suffixes and prefixes must be adjusted accordingly. و ضعنا For example, to change the past verb to its present form, the suffix is removed, and the prefix ن is added. Another example is to its present التقتا to its present form تلتقىان. Here, the suffix تا (indicating a feminine dual third person) is removed, and the suffix ان (indicating dual form) is added, along with the prefix ت to indicate a feminine third person. To convert a verb to future tense, it should first be transformed into the present is added. س is added.

Split Error In generating split errors, we consider two main approaches: 1- Randomly splitting any word at any position. For example, اهداف could be split into اهدافه، 2- Splitting specific types of words, such as: a) Interrogative words: اهدا فه would become فيما b) Conjunctions: ونفت would be split into الفلاحين, c) Pronouns: For instance, الفلاحين, would be split into

Punctuation Error In generating punctuation errors, we consider the following categories: 1- Missing punctuation: We randomly remove punctuation marks from sentences. 2- Unnecessary punctuation: We add random punctuation marks at any position within the sentence. 3- Punctuation confusion: We replace punctuation based on shape and keyboard placement. For example: The comma ","

is most likely to be replaced with "," or ";" or ".". The closing bracket"]" is likely to be replaced with "[", "(" or "}".

F Prompt Design

Designing effective prompts is fundamental to leveraging the capabilities of LLMs. A prompt, defined as a set of instructions given to an LLM, acts as a programming tool that tailors the model's responses to specific tasks (White et al., 2023). By establishing a set of specific rules and intents, prompts can significantly influence both the interactions with the model and its generated outputs. Thus, to achieve the desired outcomes, it is essential to carefully construct prompts that clearly define the task's objectives and guidelines.

To create effective prompts for our writing tasks, we designed a set of zero-shot prompts tailored to each subtask to elicit the desired responses from the models. For instance, in the I'rab task, each model was instructed to provide the complete I'rab of the sentences and explain their case markers. Similarly, for the MWEs task, models were prompted to identify and explain MWEs within sentences, including their meanings and contextual usage.

We sample 2 sentences for each subtask and use the web interfaces of all the models for the initial evaluation, focusing on the effectiveness of the prompts in eliciting the desired responses. By assessing and comparing the outputs generated by these initial prompts, we identify the most effective prompt. For most subtasks, the prompts we design successfully meet our requirements for the generated outputs.

However, the GEC prompt required a more detailed approach. Initially, we developed a zero-shot prompt instructing the models to identify the type of grammatical error in a given sentence without specifying the error types, using the prompt: "I will give you an MSA sentence with a grammatical error. You should identify the type of error, provide the correct version of the sentence, and explain the error in Arabic. The sentence:". We then use GPT-40 to iteratively refine this prompt, enhancing its ability to identify the type of error from a specified list, provide the correct version of the sentence, and explain the error. After refining, we modify the prompt and standardize it to fit all models. Detailed prompt templates we use can be found in Table G.2.

G Evaluation matrices for Arabic Writing Assistant Tasks

As mentioned earlier how we come up with the evaluation metrics of six tasks of Arabic writing assistance tasks, we provide detailed description of the metrics we employ in our evaluation. For the GEC and explanation tasks for example, we assess three specific criteria: accuracy, clarity, and helpfulness.

Accuracy refers to "the degree to which the response correctly addresses the question or task, without errors in information or execution." This criterion is rated on a scale from 1 to 5 as follows:

- 5: Completely accurate with no errors.
- 4: Mostly accurate with minor errors.
- 3: Moderately accurate with some errors.
- 2: Somewhat accurate with several errors.
- 1: Inaccurate with many errors.

Clarity indicates the ease with which the response can be understood, including how well it conveys the intended message without ambiguity. This criterion is rated on the following scale:

- 5: Extremely clear and easy to understand.
- 4: Mostly clear with minor ambiguities.
- 3: Moderately clear with some ambiguities.
- 2: Somewhat unclear with several ambiguities.
- 1: Very unclear and difficult to understand.

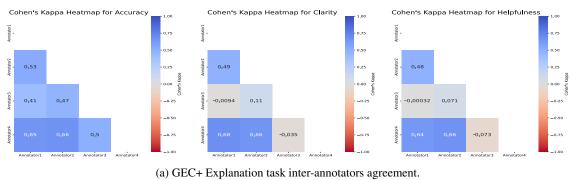
Helpfulness measures "the extent to which the response aids the user in understanding or resolving the issue, providing useful and actionable information." The scale for this criterion is as follows:

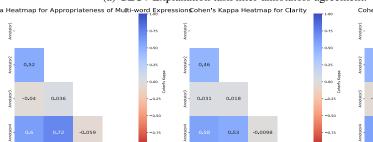
- 5: Extremely helpful and informative.
- 4: Mostly helpful with minor gaps in information.
- 3: Moderately helpful with some gaps in information.
- 2: Somewhat helpful with several gaps in information.
- 1: Not helpful and lacking useful information.

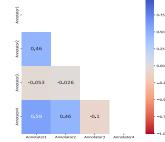
The rest of the metrics are listed in Table G.1. Figure G.1 illustrates the inter-annotator agreement for human evaluation using Cohen's Kappa metrics. Figure G.3 shows examples of responses from the four models across two different tasks.

			Gazelle Data	aset	
ALC O	Corpus	New	categories	Examp	les
Туре	Tag	Subclass	Sub2	Text with errors	Corrected text
			Medial Hamza	كانت تلك مسالة هامة.	كانت تلك مسألة هامة.
Orth.	ОН	Hamza	Hamzet Wasel The Cutting Hamzah Final Hamza	إستبشرت بالمطر خيراً. بخصوص تأمين سكن و ظيفي في احد السكنات لا يجروء المسلم على الكذب.	استبشرت بالمطر خيراً. بخصوص تأمين سكن وظيفي في أحد السكنات لا يجرؤ المسلم على الكذب.
ax		Plural	Masculine Sound Plural Almaqsour Plural	سائقوا السيارات ملتزمون بتعليمات إدارة المرور. وعلى مرمى طوبة زمن منا ونحن لا نعيه، بُلُهَاء لا ندركه.	سائقو السيارات ملتزمون بتعليمات إدارة المرور. وعلى مرمى طوبة زمن منا ونحن لا نعيه، بُنُهُ لا ندركه.
Synt	XN	Number	Composite Numbers Al Aqoud	يمكنكم الأن مشاهدة الحلقة الثالثة عشر حضر مريض في الخمسون من عمره.	يمكنكم الأن مشاهدة الحلقة الثالثة عشرة حضر مريض في الخمسين من عمره.
			Adding Unnecessary Prepositions	تحرى فلان عن الأمر.	تحرى فلان الأمر.
itics	SW	Word Selection Error	Removing Necessary Prepositions	تسعى الدو لة تحقيق مكاسب دو لية.	تسعى الدو لة إلى تحقيق مكاسب دو لية.
ma			Replacing Prepositions	ثم وجدت طلبا في بلاد مختلفة.	ثم وجدت طلبا من بلاد مختلفة.
š			Adding Unnecessary Conjunction	ووصلت صدى هذه الأصوات حتى إلى قلوب بعض المسلمين والمسلمات.	ووصلت صدى هذه الأصوات إلى قلوب بعض المسلمين والمسلمات.
	SF	Conjuction Error	Removing Necessary Conjunction	اذهب إلى فلان وقل له كذا.	اذهب إلى فلان فقل له كذا.
	РО	Other Punctuation	Comma (,)	فضلاًا عن ذلك ، عبّر عن رأيه بأسلوب سلس.	فضلاًا عن ذلڪ ، عبّر عن رايه باسلوب سلس.
ШC.	PC	Commission Errors	Full Stop (.)	الشمس تزود الأرض بالحرارة والضوء ؟	الشمس تزود الأرض بالحرارة والضوء.
d,	PM	Misuse of Punctuation Marks	Question Marks (?)	هل يستطيع هذا القس أن يعلن ر غبته	هل يستطيع هذا القس أن يعلن رغبته ؟

Table F.1: Comparison of *Gazelle* with examples taken from the QALB 2014, QALB 2015, and ZAEBUC datasets, all of which are based on the ALC error taxonomy. *Gazelle* provides more fine-grained and specific error type coverage within this taxonomy.*Sub2 represents our extended subclass within the ALC error types. *Orth.: Orthography *Punc.: Punctuation.

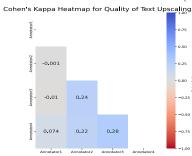




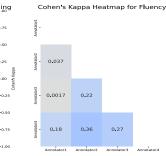


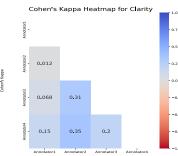
n's Kappa Heatmap for Relevand

(b) MWE task inter-annotators agreement.

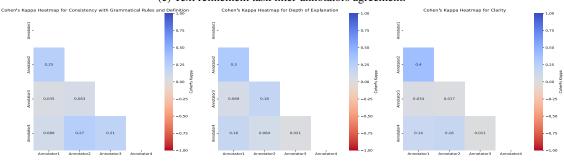


Cohen's Kap

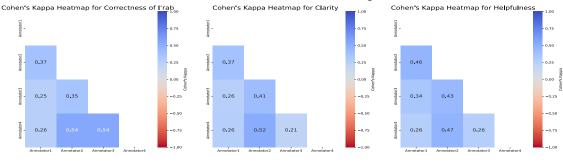




(c) Text refinement task inter-annotators agreement.



(d) Grammatical Rules task inter-annotators agreement.



(e) I'rab task inter-annotators agreement.

Figure G.1: Inter-annotator agreement for human evaluation using Cohen's Kappa.

Grammatical Error Correction & Explanation
Correct any grammatical errors in the given sentence, ensuring it is written correctly in Arabic. Identify and assign the error and type of errors to the provided list of errors, explain the error, and be more specific.
The sentence: الحقُّ يعلو ولا يُعلا عليه. \n\n\n
List of error types: - Orthographic
- Syntax
- Morphology
- Semantics - Punctuation
- Pantaauon
- Split
The output should be in the following JSON format:
t "correction": corrected sentence,
"error": error in the sentence,
"error_type": error in the sentence from the list of error types with more details,
"explanation": explanation of the error.
Multi Word Expressions and Metaphors
Correct the errors in the sentence and and specifically the use of multi-word expressions or idioms. Explain the error and
identify the part containing it. "بمع تقدم العمر، وتراكم المسؤوليات، تسللت منها هموم لا مفر منها، تفرض نفسها على كل جانب من جوانب حياتها".
Grammatical Rules & Definition
Answer the following question about Arabic grammatical rules and definitions in Arabic.
ما هو الفعل الأجوف؟ :The question
l'rab
حدد الإعراب الكامل للجملة المعطاة
الجملة: ما جاء التلاميذ سوى تلميذين
Tout Un Spaling
Text- Up Scaling
Rewrite the following text in formal Arabic, being careful to avoid colloguial words.
reavring the following text in formal Arabic, being careful to avoid conoquial words. الجملة: و المدام أيضاً جاءت بخصوص الإعلان الذي في الجريدة؟

Figure G.2: Prompts used for LLMs evaluation.

Task	Measures	Scale Details
	incusures	5: Completely accurate with no errors.
Grammar Error Correction+Explanation		4: Mostly accurate with minor errors.
cpla	Accuracy	3: Moderately accurate with some errors.
+Ex		2: Somewhat accurate with several errors.1: Inaccurate with many errors.
tion		5: Extremely clear and easy to understand.
Tect		4: Mostly clear with minor ambiguities.
Cor	Clarity	3: Moderately clear with some ambiguities.
ror		2: Somewhat unclear with several ambiguities.
Ъ		1: Very unclear and difficult to understand.
nma		5: Extremely helpful and informative.4: Mostly helpful with minor gaps in information.
ran	Helpfulness	3: Moderately helpful with some gaps in information.
0	1	2: Somewhat helpful with several gaps in information.
		1: Not helpful and lacking useful information.
		5: Extremely appropriate and contextually fitting.
	Appropriateness of	4: Mostly appropriate with minor issues.
	Multi-word Expressions	 3: Moderately appropriate with some issues. 2: Somewhat appropriate with several issues.
suo		1: Inappropriate and contextually unfitting.
Multi-word Expressions		5: Extremely clear and easy to understand.
xpro		4: Mostly clear with minor ambiguities.
Эp	Clarity	3: Moderately clear with some ambiguities.
wor		2: Somewhat unclear with several ambiguities.
-ifi		1: Very unclear and difficult to understand. 5: Completely relevant to the task/question.
M		4: Mostly relevant with minor off-topic elements.
	Relevance	3: Moderately relevant with some off-topic elements.
		2: Somewhat relevant with several off-topic elements.
		1: Irrelevant to the task/question.
		5: Completely correct with no errors.
		4: Mostly correct with minor errors.
	Correctness of I'rab	3: Moderately correct with some errors.
		2: Somewhat correct with several errors.
		1: Incorrect with many errors.
		5: Extremely clear and easy to understand.
ab	Clarity	4: Mostly clear with minor ambiguities.3: Moderately clear with some ambiguities.
I'rab	Charity	2: Somewhat unclear with several ambiguities.
		1: Very unclear and difficult to understand.
		5: Extremely helpful and informative.
	TT 1 C 1	4: Mostly helpful with minor gaps in information.
	Helpfulness	3: Moderately helpful with some gaps in information.2: Somewhat helpful with several gaps in information.
		1: Not helpful and lacking useful information.
		5: Completely consistent and correct.
	Consistency with	4: Mostly consistent with minor inconsistencies.
su	Grammatical Rules and	3: Moderately consistent with some inconsistencies.
itio	Definitions	2: Somewhat consistent with several inconsistencies.
efin		1: Inconsistent and incorrect.
О +		5: Extremely thorough and detailed.4: Mostly thorough with minor details missing.
ule	Depth of Explanation	3: Moderately thorough with some details missing.
al R		2: Somewhat thorough with several details missing.
Grammatical Rule + Definition		1: Superficial and lacking in detail.
nm		5: Extremely clear and easy to understand.
Jrai	Clarity	4: Mostly clear with minor ambiguities.3: Moderately clear with some ambiguities.
<u> </u>	Jainty	2: Somewhat unclear with several ambiguities.
		1: Very unclear and difficult to understand.
		5: Extremely high quality with significant improvement.
		4: High quality with notable improvement.
	Quality of Text Upscaling	3: Moderate quality with some improvement.
		2: Low quality with minimal improvement.1: Poor quality with no improvement or degradation.
50		5: Extremely fluent and natural.
alin		4: Mostly fluent with minor awkwardness.
psc	Fluency	3: Moderately fluent with some awkwardness.
Text Upscaling		2: Somewhat fluent with several awkward phrases.
Tey		1: Not fluent and very awkward.
		5: Extremely clear and easy to understand.
	Clarity	4: Mostly clear with minor ambiguities.3: Moderately clear with some ambiguities.
	Juny	2: Somewhat unclear with several ambiguities.
		1: Very unclear and difficult understand.

Table G.1: Evaluation criteria we employ for Arabic writing assistance tasks in our work.

Online Sources

http://www.al-musheer.com/play-735.html
https://www.wuduh1.com/2023/09/constructive-style.html
https://learning.aljazeera.net/ar/grammar
https://loghate.com/
https://www.twinkl.ae/teaching-wiki/hmzt-alwsl-whmzt-alqt

Table G.2: List of some of the publicly available online sources used in collecting Gazelle dataset.

	Prompt	GPT-40 response	Cohere Command R+ response	GPT-4 response	Gemini 1.5 Pro response
Correct any g sentence, and values and values (and value). Justino syspe of errors applicable of errors applicable of errors applicable of errors applicable of the sentence in the sentence of the sentence value. The sentence value of the sentence sentence of the sentence correction of error of the correction of error of the sentence of the sentence of the sentence of the sentence of the sentence of the sentence of the sentence of the sentence of the sentence of the sentence of the sentence of the sentence of the sentence of the sentence of the sentence of the se	Correct any grammatical errors in the given sentence, ensuing it as whiten correctly in Apped tearity and as sup the error and type of tearity and as sup the error and here are and be more specific. In the sentence sup the more specific. The more are and be more specific. The more are are and be more specific. The more area are and be more specific. The rest of error types is something. Support Signations are area are are are sentor, corrected sentence, "error: prose with more dealing." "error: prose with more dealing." "error: prose with more dealing." "error: prose with more dealing." "error: prose with more dealing."	المعلين "correction" { "حديث": المحلية "error_type" "Syntax - Gender "error_type" "Syntax - Gender "reculture and "The word" is ferminute but "cut" is masculture the correct form should be "a" to match the gender of "cut" "	الحدى مكرنات المدلية" (مدى مكرنات المدلية من المالية" "correction", "شاملية من المدلية المدلية المدلية من المدلية ا مالية المدلية الم مالية المدلية	احدى مكونات المدلية" : "correction" " الممليعة" "لا يوجد خطا": "عبرا النحية المحوية والالالية والدلالية الناحية المحوية والالالية والدلالية. " يوجد خطا لتصحيمه الناحية المحوية (العدارين المدلية " المحالية". "correction": "تركيمية "error": "تركيمية "error": "Crhub Error": "Crho Purcundon", "explanation": "The word (خماية "explanation": "The word (خماية "explanation": "The word (خماية should be written with a full stop (ر)" " ()"
₽ *	. حدد الإمراب الكامل للجملة المعطاة ". الجملة: أنت تشيط في المدرسة	بالتا كين، سالاوم بتحديد الإعراب الكمل للجملة المحلقة المحلقة المحلقة على الحرب على الحرب المدر سابح المحلم وليه المحمة الطاهرة المدر سابح المحل المحل الحرب المدر سابح المحل المحل المحل الع المحل المحرب المدر سابح المحرور و يعرف المر "في" و عالمة المدر سابح المحرور يعرف المر" في و عالمة المدر المحرة الطاهرة على أذره المدر المحرة الطاهرة على أذره	إعراب الجملة: أنت تسيّل في المرسية ##" (إكماب الكمل للجملة "أنت تشميط في الأكمان للجملة "أنت تشميط في المدرسة" المدرسة المحمد المحمد المحمد المحمد الحمد الحمد الحمد الحمد الحمد الحمد الحمد التي في محمد إذ الحمد الحمد الحم المدرسة المحمد الحمد الحمد المدرسة الحمد الحمد المدرسة الحمد الحمد المدرسة الحمد الحم المدرسة الحمد الحمد حمد حمد حمد حمد حمد حمد حمد حمد حمد	الإعراب (الكمل للجملة ""انت تشيط ق" المدرسة"" هو كانتان فت: ضمير مخلطب بېنى السطى في مطل الشيط: خير الصيبية في التان 	الجراب الجملة: أنت تشيكا في المدرسة ##* ***: فتسبير رايم بنفسل بني على ** **: يتبيليه* المدرية الأهرو على على المكرن لمه** ***: المدرية الأهرو على المكرن لمه** ***: المدرية المالي مر حرور يحرف الحرو** ***: المدرية *** ***: المدرية *** ***: المدرية *** ***: المدرية *** ***: المدرية ***

Figure G.3: Sample model responses for GEC, explanation, and I'rab tasks.

Task	Accuracy	Clarity	Helpfulness	Appropriateness of MWEs	Relevance	Consistency with Gr. Rules and Definition	Depth of Explanation	Correctness of l'rab	Quality of Text Refinement	Fluency
GEC Cohere	2.80	3.28	3.25							
GEC GPT4	2.02	3.17	2.90							
GEC GPT40	3.27	3.77	3.63							
GEC Gemini15pro	2.70	3.18	3.03							
MWEs Cohere		3.68		3.15	3.78					
MWEs GPT4		3.25		2.63	3.28					
MWEs GPT40		3.89		3.46	3.91					
MWEs Gemini15pro		3.38		2.91	3.36					
Gr. Rules Cohere		4.20				3.74	4.03			
Gr. Rules GPT4		3.23				2.95	3.11			
Gr. Rules GPT40		4.73				4.58	4.66			
Gr. Rules Gemini15pro		4.22				4.01	4.33			
I'rab Cohere		4.41	4.40					3.91		
I'rab GPT4		3.59	3.44					3.01		
I'rab GPT40		4.68	4.71					4.39		
I'rab Gemini15pro		3.73	3.83					3.65		
Text Cohere		3.48							3.20	3.39
Text GPT4		3.54							3.15	3.49
Text GPT40		3.91							3.55	3.70
Text Gemini15pro		3.47							3.39	3.47

Table G.3: Evaluation results for the five subtasks across all LLMs.