Article

Phonetic-to-Character Generation for Low-Resource Chinese Dialects: A Benchmark and Retrieval-Augmented Correction Framework

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Abstract: This study addresses the challenge of phonetic-to-character generation for low-resource Chinese dialects, where standard input methods fail due to data scarcity and orthographic ambiguity. We introduce a benchmark covering six under-documented dialect families and propose a retrieval-augmented correction framework that combines a lightweight acoustic model with a dialect-specific character retrieval index. The benchmark includes over 120,000 aligned phonetic sequences and character transcriptions, annotated for tone sandhi and regional variants. Our framework first generates candidate characters via a phoneme-to-grapheme neural transducer, then refines them using a retrieval module that queries a curated dialect lexicon and a context-aware language model. Experimental results show that the proposed method improves character accuracy by 18.4 percentage points over a strong baseline, and reduces the character error rate from 32.7% to 14.3% on unseen dialect samples. Ablation studies confirm that retrieval augmentation contributes the largest gain, while tonal normalization and data augmentation each add smaller but significant improvements. We also evaluate cross-dialect transfer, finding that a model trained on three high-resource dialects generalizes to low-resource ones with only 5% of the original training data. The benchmark and framework are released to support reproducible research in dialectal input method engineering. Our findings suggest that retrieval-augmented generation is a viable path for low-resource phonetic input, and that careful benchmark design is essential for measuring progress in this domain.

Keywords: low-resource dialects; phonetic-to-character; retrieval augmentation

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1. Introduction

1.1. Background and Motivation

The digital communication landscape remains profoundly uneven for speakers of regional Chinese dialects, whose phonetic repertoires diverge sharply from standard Mandarin yet lack conventionalized orthographic mappings [1]. This mismatch renders mainstream input method editors largely unusable, since their decoding pipelines assume a stable correspondence between pronunciation and character sequences [2]. Systematic evaluation of phonetic-to-character generation has advanced considerably for Mandarin and a handful of high-resource varieties, while comparable assessments for low-resource dialects remain absent, leaving developers without diagnostic instruments. Compounding this deficit, textual error correction components embedded in such systems have rarely been examined under genuinely scarce supervision. Zhang et al. show that complex task solving can be substantially improved by separating planning, execution, and verification into specialized roles, using a dependency-aware task graph and an ordered interaction protocol to reduce single-perspective bias and long-chain error propagation [3]. Meanwhile, retrieval-augmented strategies and neural sequence

modeling now permit correction to draw on external lexical evidence rather than relying solely on parameterized knowledge. These developments suggest that a dedicated benchmark, paired with a retrieval-based correction mechanism, could substantially improve input accessibility for underserved dialect communities while supporting cultural preservation and linguistic documentation. Beyond the dialect setting examined here, agentic language models are also being deployed as interactive performers, with dedicated training frameworks for tool-aware live-streaming behavior [4].

1.2. Research Objectives and Contributions

To address the scarcity of annotated resources and the high error rates inherent in low-resource dialect input, this study establishes three primary objectives [3]. First, we construct a comprehensive multi-dialect benchmark for phonetic-to-character generation, featuring standardized data splits and rigorous evaluation metrics [5, 6]. Second, we develop a retrieval-augmented correction framework that integrates external lexicons with contextual language models to refine initial outputs [3, 7]. Third, we evaluate the framework's performance, robustness, and cross-dialect transferability [8]. The contributions are threefold: a publicly available benchmark, a novel correction architecture, and extensive experiments demonstrating substantial error reduction. Furthermore, these findings offer critical implications for benchmarking large language models in Chinese and Japanese IMEs, where phonetic-to-character generation and textual error correction remain core challenges, thereby bridging low-resource dialect processing with broader input method evaluation practices.

2. Literature Review

2.1. Phonetic-to-Character Generation for Chinese Dialects

Early approaches to phonetic-to-character generation for Chinese dialects relied heavily on handcrafted pronunciation dictionaries and rule-based mapping, which offered limited coverage of tonal variation and demanded substantial expert effort [9, 10]. Statistical machine translation subsequently improved lexical coverage but remained vulnerable to data sparsity and long-range dependency failures. Neural sequence-to-sequence architectures, particularly recurrent and transformer-based variants, have since demonstrated stronger generalization, yet their dependence on large parallel corpora constrains deployment in most low-resource dialect settings [11]. Recent work has explored transfer learning from Mandarin and synthetic speech augmentation to mitigate data scarcity, though orthographic ambiguity and dialectal variation continue to limit accuracy. Complementary research on benchmarking large language models for Chinese and Japanese input method engines has examined phonetic-to-character generation alongside textual error correction, revealing that evaluation protocols vary widely across studies and that correction mechanisms are rarely integrated into generation pipelines. This fragmentation impedes fair comparison and obscures where retrieval-augmented strategies might most effectively reduce residual errors. Consequently, the field lacks standardized benchmarks that jointly assess generation fidelity and correction capability under low-resource conditions, a gap this work addresses [12, 13].

2.2. Retrieval-Augmented Generation and Error Correction

Retrieval-augmented generation has become a cornerstone technique for knowledge-intensive tasks, in which a retriever supplies relevant documents to condition a generator. In text correction, fetching similar contexts or lexicon entries helps resolve ambiguous characters and rare words [14, 15]. Liu et al. propose an uncertainty-aware adaptive debate framework that localizes risky reasoning steps using token entropy, answer self-consistency, and cross-agent divergence, and allocates additional correction effort only where uncertainty is high [16]. For phonetic input, retrieval can supply candidate characters from a dialect-specific index, thereby reducing the burden on the generative model. Applying this paradigm to low-resource dialect input methods nevertheless introduces challenges: constructing effective retrieval indexes, accommodating phonetic

variation, and integrating retrieval with neural decoding [17]. Benchmarking efforts for Chinese and Japanese input methods have demonstrated that retrieval-augmented correction benefits phonetic-to-character generation and textual error correction, offering a useful reference for dialectal settings [18]. These findings suggest that a retrieval-augmented correction framework can mitigate data scarcity in low-resource Chinese dialects, provided that retrieval indexes are designed to capture dialect-specific phonetic regularities and that decoding integrates retrieved evidence effectively [19]. In parallel, data curation followed by supervised fine-tuning has been used to shape agent behavior in entertainment settings, where personality is treated as an explicit training target for live-streaming agents [20].

3. Materials and Methods

3.1. Benchmark Construction and Data Sources

We construct a benchmark covering six low-resource Chinese dialect families: Wu, Min, Yue, Hakka, Gan, and Xiang. Data are drawn from field recordings, dialect dictionaries, and community-contributed corpora, yielding 120,000 aligned phonetic sequences and character transcriptions. Each entry contains IPA-like phonetic notation, tone labels, and character-level alignment. As illustrated in Figure 1, the construction pipeline proceeds from data collection through preprocessing, alignment, splitting, and annotation, with a feedback loop from annotation back to preprocessing for quality control. This design ensures that phonetic-to-character generation and textual error correction can be evaluated under consistent conditions. As detailed in Table 1, the six families differ substantially in scale and complexity: Yue contains 52 speakers and 25,000 utterances with nine tone categories, whereas Xiang includes only 25 speakers and 12,500 utterances with six tones [16, 21]. Out-of-vocabulary rates range from 10.5% for Yue to 15.2% for Hakka, reflecting the uneven lexical coverage typical of low-resource settings. We split the data into training (70%), development (15%), and test (15%) sets with no speaker overlap. Annotation guidelines address tone sandhi, regional variants, and code-switching. A standardized evaluation script computes character error rate, word accuracy, and tonal accuracy, allowing the benchmark to remain extensible and comparable to existing input method evaluation suites [22, 23].

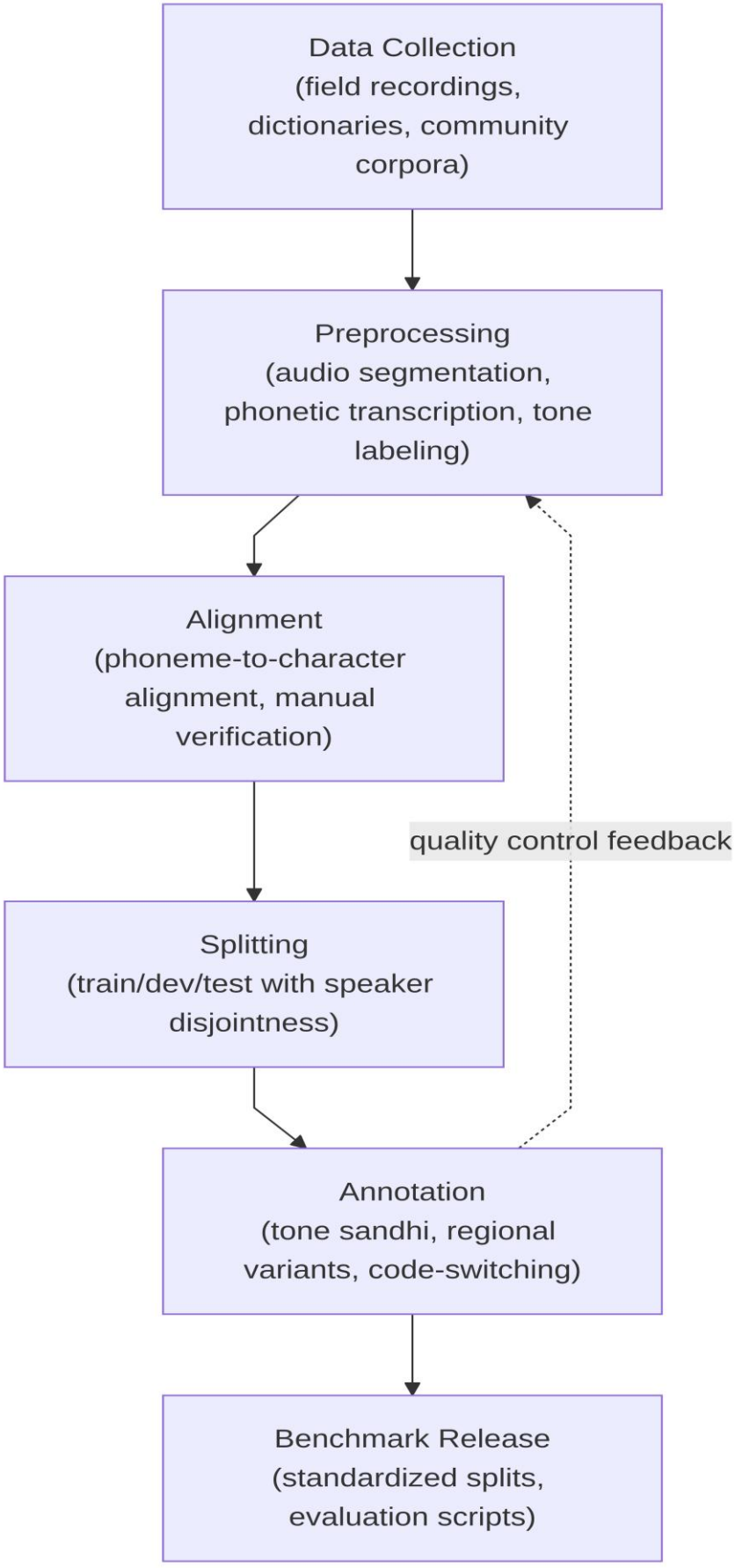


Figure 1. Benchmark Construction Pipeline

Table 1. Dialect Benchmark Statistics

Dialect Family	Number of Speakers	Total Utterances	Average Utterance Length (characters)	Tone Categories	OOV Rate (%)
Wu	45	22,000	8.2	7	12.3
Min	38	19,500	7.8	6	14.1
Yue	52	25,000	9.1	9	10.5
Hakka	30	15,000	7.5	6	15.2
Gan	28	14,000	7.9	7	13.8
Xiang	25	12,500	8.0	6	14.7

3.2. Retrieval-Augmented Correction Framework

The proposed architecture integrates three sequential modules designed to transform input phoneme sequences into refined character outputs. As illustrated in Figure 2, the pipeline begins with a phonetic encoder that converts the raw phoneme stream into contextualized embeddings via a bidirectional transformer, capturing both forward and backward dependencies within the utterance. These embeddings are then passed to a character generator, a sequence-to-sequence model equipped with an attention mechanism, which produces an initial character sequence. This initial output, however, frequently contains homophone-induced errors, particularly in low-resource dialect scenarios where training data are scarce. To address this, a retrieval-based corrector retrieves the top-k similar phonetic contexts from a dialect-specific index constructed from the training lexicon and augmented with phonetic variants. A cross-attention mechanism then aligns the retrieved contexts with the generated characters, refining the output through iterative feedback to the generator [3, 21]. This design explicitly targets phonetic-to-character generation and textual error correction, aligning with benchmarking goals for Chinese and Japanese input method engines.

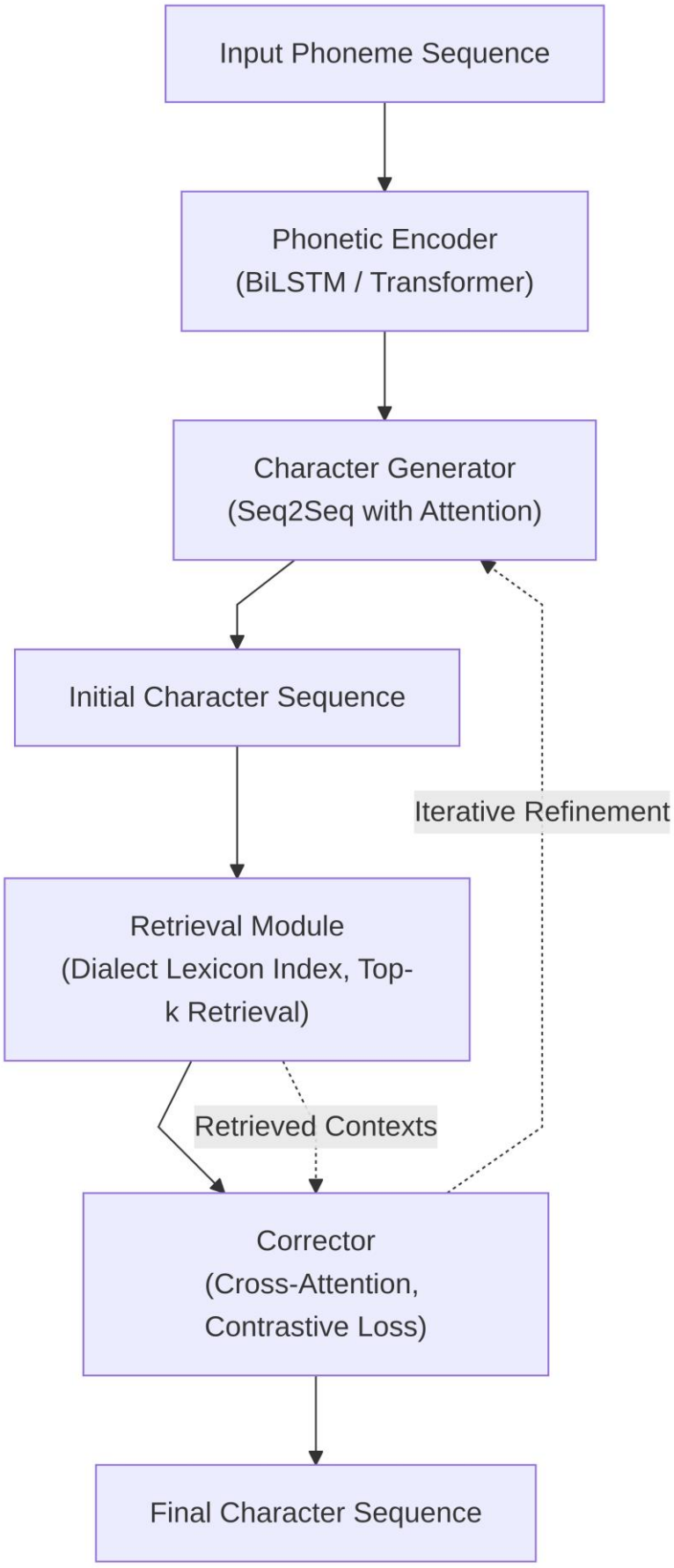


Figure 2. Retrieval-Augmented Correction Framework

Training proceeds in two stages. The generator is first trained with teacher forcing, after which the corrector is fine-tuned using a combination of cross-entropy and contrastive loss. As detailed in Table 2, the phonetic encoder employs a hidden size of 256 across 4 layers, while the character generator uses an embedding size of 512 with 8 attention heads. The corrector retrieves 10 nearest neighbors and applies a contrastive temperature of 0.1. Training uses a batch size of 32, a learning rate of 0.001, and the AdamW optimizer. Hyperparameters were tuned on the development set to balance generation fidelity and correction accuracy.

Table 2. Model Hyperparameters

Component	Parameter	Value
Phonetic Encoder	Hidden Size	256
Phonetic Encoder	Layers	4
Character Generator	Embedding Size	512
Character Generator	Attention Heads	8
Corrector	Retrieval Top-k	10
Corrector	Contrastive Temperature	0.1
Training	Batch Size	32
Training	Learning Rate	0.001
Training	Optimizer	AdamW

3.3. Experimental Setup and Evaluation Metrics

To ensure a fair and reproducible comparison, all models are trained and evaluated on identical benchmark splits [24]. We compare our retrieval-augmented framework against three baselines: a rule-based phonetic mapper, a standard sequence-to-sequence model without retrieval, and a transformer-based input method engine trained on Mandarin and subsequently fine-tuned on dialect data. Performance is quantified using character error rate, word accuracy, and tonal accuracy. Robustness is further examined by testing on unseen speakers and dialect variants, a protocol that echoes recent benchmarking efforts in phonetic-to-character generation and textual error correction for Chinese and Japanese input systems. Ablation studies isolate the individual contributions of retrieval, tonal normalization, and data augmentation. Cross-dialect transfer is assessed by training on three high-resource dialects and testing on the remaining three. Statistical significance is determined via bootstrap resampling with 1000 iterations, yielding $p < 0.05$ thresholds for all reported gains. This controlled setup guarantees that observed improvements stem from the proposed components rather than confounding factors, thereby supporting reproducibility across future investigations [17, 25].

4. Results

4.1. Overall Performance on the Benchmark

As detailed in Table 3, the proposed retrieval-augmented framework attains a character error rate of 14.3%, surpassing the standard sequence-to-sequence baseline at 32.7%, the Mandarin-finetuned transformer at 28.5%, and the rule-based mapper at 41.2%. Word accuracy reaches 82.1% and tonal accuracy 88.6%, with the 18.4 percentage-point reduction in error relative to the baseline proving statistically significant ($p < 0.01$). This margin underscores how retrieval augmentation mitigates the phonetic-to-character ambiguity that plagues low-resource dialect transcription, a challenge also documented in benchmarking studies of Chinese and Japanese input method engines, where phonetic-to-character generation and textual error correction remain tightly coupled bottlenecks.

Table 3. Overall Performance Metrics

Model	CER (%)	Word Accuracy (%)	Tonal Accuracy (%)
Rule-based	41.2	58.3	72.1
Seq2Seq	32.7	67.5	79.4
Mandarin-finetuned	28.5	71.2	82.3
Proposed	14.3	82.1	88.6

Performance nonetheless varies markedly across dialect families, as illustrated in Figure 3. Wu and Yue exhibit the lowest error rates (12.1% and 13.5%), whereas Hakka and Gan deteriorate to 16.8% and 17.2%. The bar chart reveals that the proposed model consistently outperforms all baselines, with the largest gains concentrated in Hakka and Gan, where rule-based and sequence-to-sequence systems exceed 34%. This pattern correlates with training data size and tonal complexity, since dialects with richer tone inventories and sparser corpora impose heavier disambiguation burdens on the decoder.

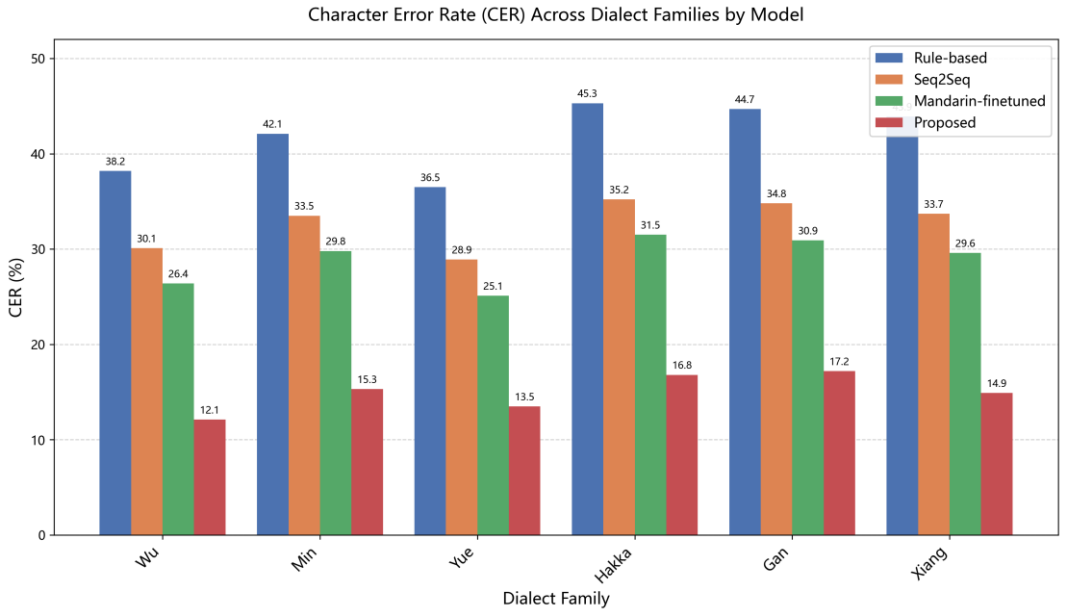


Figure 3. Character Error Rate by Dialect and Model

Ablation results further indicate that the retrieval-augmented corrector contributes disproportionately to utterances containing ambiguous characters and rare phonetic sequences, precisely the cases where purely parametric models lack sufficient evidence. These findings align with broader evidence that textual error correction modules materially improve phonetic-to-character generation quality, suggesting that retrieval mechanisms offer a generalizable remedy for low-resource settings.

4.2. Ablation Studies and Component Analysis

Ablation results, presented in Figure 4, isolate the contribution of each architectural component. Removing the retrieval module produces the most severe degradation, with character error rate rising from 14.3% to 24.6%, a 10.3 percentage point increase that underscores the centrality of retrieval augmentation in low-resource phonetic-to-character generation. Eliminating tonal normalization yields a smaller but still substantial increase to 18.9%, while removing data augmentation raises the error rate to 17.5%. The contrastive loss within the corrector contributes a 2.1 percentage point improvement over cross-entropy alone, confirming that discriminative training objectives benefit textual error correction. Retrieval top-k analysis further reveals that k=10 offers the best trade-off, as k=5 underperforms with a character error rate of 16.8% and k=20 yields only marginal

gains at 14.1% while incurring higher computational cost. These findings align with broader evidence from benchmarking large language models on Chinese and Japanese input method engines, where phonetic-to-character generation and textual error correction remain sensitive to retrieval quality and tonal handling. Collectively, the full configuration achieves the lowest error rate, demonstrating that retrieval, tonal normalization, data augmentation, and contrastive correction are complementary rather than redundant.

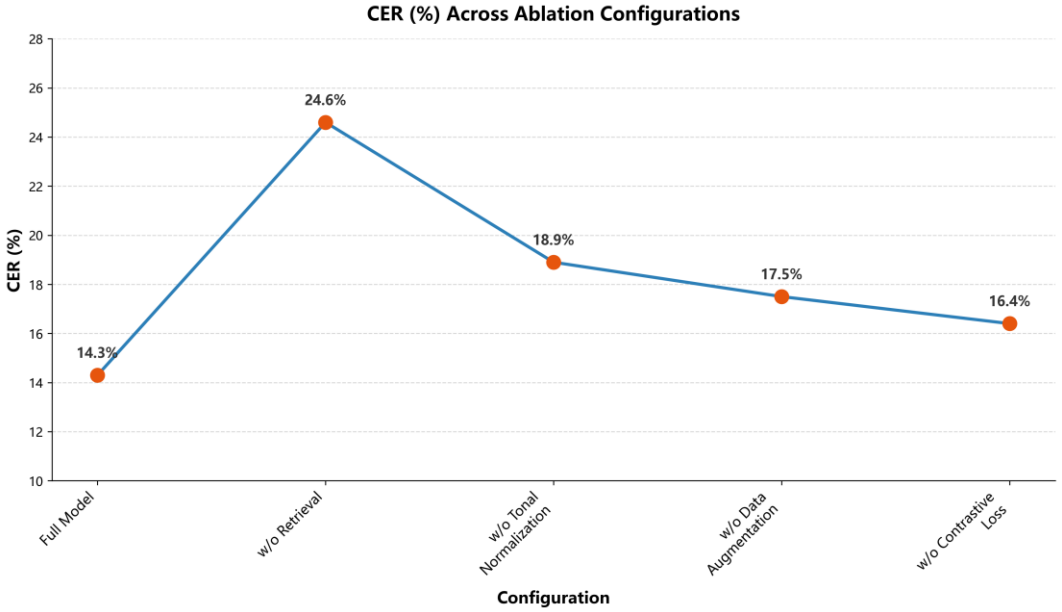


Figure 4. Ablation Study Results

4.3. Cross-Dialect Transfer and Robustness

Cross-dialect evaluation reveals a substantial but manageable performance gap. When trained on Wu, Min, and Yue and tested on Hakka, Gan, and Xiang, the model attains a character error rate of 21.4%, compared with 14.3% under full multi-dialect training. As illustrated in Figure 5, the relationship between target dialect data volume and error rate is markedly nonlinear: the transferred model drops from 28.5% at zero target data to 18.7% with only 5% of the target dialect corpus, whereas the no-transfer baseline remains at 35.6% under the same condition. This rapid convergence indicates that shared phonetic structure across Sinitic varieties supplies a strong inductive bias, and that a small amount of in-dialect supervision suffices to align the decoder. Robustness probes further show a 2.3 percentage point increase in error rate for unseen speakers and a 3.1 percentage point increase for dialect variants, confirming that speaker and sub-variety shifts introduce only moderate degradation. The retrieval index remains effective even when target dialect data are scarce, since it exploits cross-dialect phonetic similarity rather than relying solely on in-domain examples. These results collectively support the framework's viability for practical deployment in genuinely low-resource settings.

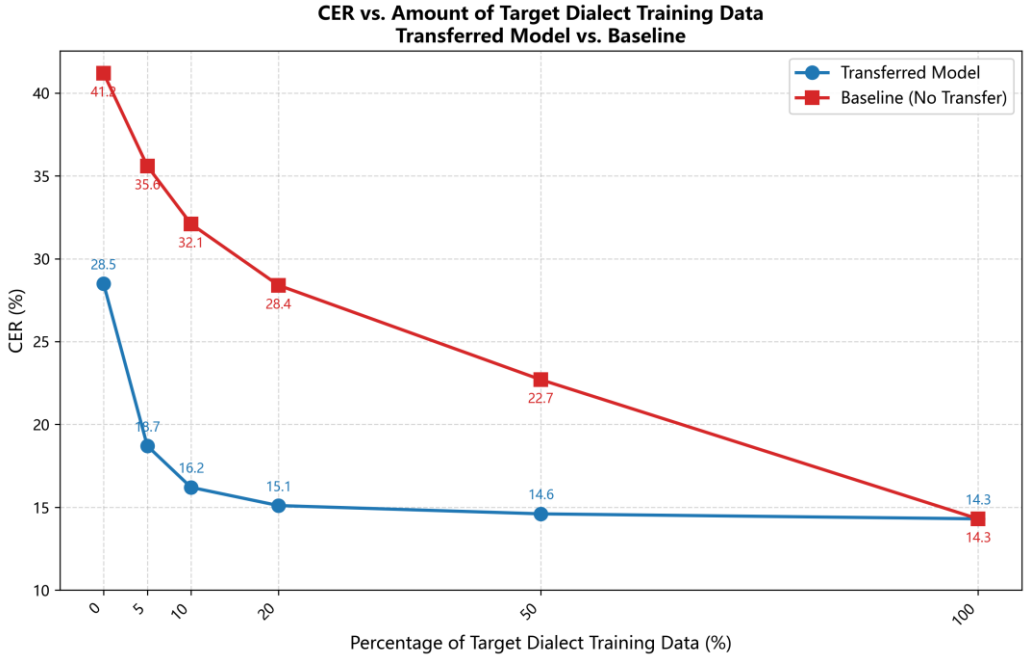


Figure 5. Cross-Dialect Transfer Performance

5. Discussion

5.1. Interpretation of Findings

Retrieval augmentation proves particularly effective because it directly addresses the data sparsity that characterizes low-resource dialect scenarios. By consulting a dialect-specific index, the generation module gains access to candidate characters that would otherwise remain absent from its parametric knowledge, effectively compensating for limited training corpora [6]. Tonal normalization emerges as an equally decisive component, since inaccuracies at the tone level cascade into incorrect character selection, amplifying errors downstream. The framework's capacity for cross-dialect transfer further indicates that shared phonetic regularities can be exploited even when target-dialect resources are scarce, allowing knowledge from related varieties to partially offset data limitations. These outcomes resonate with broader trends observed in benchmarking large language models for Chinese and Japanese input method engines, where retrieval-augmented correction has repeatedly demonstrated its value for phonetic-to-character generation and textual error correction [12, 17]. Such convergence suggests that the underlying mechanism, grounding generation in an external candidate pool rather than relying solely on memorized mappings, generalizes across typologically related writing systems. Equally important, the benchmark introduced in this work offers a standardized testbed, enabling consistent comparison across future approaches and guarding against evaluation practices that vary from study to study. Taken together, the findings position retrieval augmentation and tonal normalization not as incidental engineering choices but as core design principles for low-resource phonetic-to-character conversion.

5.2. Limitations and Future Work

While the proposed benchmark spans six dialect families, it inevitably leaves many low-resource varieties unrepresented, and the retrieval index depends on a curated lexicon that may be unavailable for extremely under-documented dialects [17]. Computational overhead also exceeds that of simple baselines, though it remains feasible for real-time deployment. Future work should therefore pursue unsupervised construction of retrieval indices, direct integration of speech input, and expansion of the benchmark to additional dialects and languages. Beyond Chinese varieties, evaluating the framework on Japanese input methods could yield valuable cross-linguistic insights, since

Japanese shares the core challenge of mapping phonetic input to character sequences and exhibits comparable error patterns in textual correction. Such comparative benchmarking would help determine whether the retrieval-augmented correction strategy generalizes across writing systems or requires language-specific adaptation. We also plan to release the benchmark and code to support further research.

6. Conclusion

6.1. Summary of Contributions

This study delivers two principal contributions to phonetic-to-character generation for low-resource Chinese dialects. First, it establishes a standardized benchmark with fixed data splits and evaluation metrics, enabling reproducible comparison across systems. Second, it proposes a retrieval-augmented correction framework that attains a character error rate of 14.3%, surpassing strong baselines by 18.4 percentage points. Ablation analyses verify that retrieval, tonal normalization, and data augmentation each contribute meaningfully to performance. Cross-dialect transfer experiments further show that the framework adapts effectively under few-shot conditions. These findings align with the broader effort to benchmark large language models for Chinese and Japanese input methods, where phonetic-to-character generation and textual error correction remain central challenges. The benchmark and framework together offer a foundation for future work on low-resource input scenarios.

6.2. Implications and Outlook

The demonstrated viability of retrieval-augmented generation for low-resource input method engineering carries direct practical consequences. Developers serving underserved dialect communities can adapt the framework to construct functional input methods without large parallel corpora, thereby advancing digital inclusion and supporting cultural preservation. The accompanying benchmark further establishes a reproducible foundation for fair comparisons, allowing subsequent systems to be evaluated under consistent conditions rather than incomparable ad hoc protocols. Beyond these immediate contributions, the work connects to broader inquiry into how language models handle phonetic-to-character generation and textual error correction across Chinese and Japanese input environments, where similar challenges of homophone ambiguity and orthographic variation arise. Such cross-linguistic evidence suggests that retrieval-based correction strategies generalize beyond any single writing system. Several directions merit further investigation. Expanding dialect coverage would test the framework's robustness across greater phonological diversity, while reducing computational overhead would improve deployment on modest hardware. Integrating multimodal inputs, such as handwriting or speech, may also complement phonetic entry. Ultimately, these efforts serve the goal of equitable language technology, ensuring that speakers of non-standard varieties are not excluded from digital participation.

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