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Research on an AI-Based Platform for Proofreading and Writing Style Learning of Digital Content

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Abstract
While recent Large Language Models (LLMs) have demonstrated exceptional capabilities in language generation and correction, they often struggle to preserve an author's unique writing style and literary creativity—especially regarding experimental expressions and intentional rule-breaking. Existing AI-based systems typically prioritize grammatical and formal consistency, frequently standardizing or removing the stylistic deviations essential to literary creation. To address these limitations, this study proposes a writing style-aware LLM customization framework utilizing lightweight LoRA fine-tuning. The platform integrates a writing style analyzer, style-aware dataset construction, exception handling for experimental expressions, and personalized fine-tuning based on a Gemma 3 LLM. Implemented as a four-layer architecture, the system supports continuous user interaction and feedback. Experimental results using works from a professional novelist indicate that the model's outputs align with the author's intended style at an agreement rate of approximately 80%. These findings demonstrate the feasibility of an inclusive AI-assisted creative system that preserves authorial individuality and literary freedom.
Keywords: *Large Language Models(LLMs), Writing Style Learning, Personalized LoRA Fine-Tuning, Creative Writing Assistance, Literary Expression Preservation,*

1. INTRODUCTION

The rapid advancement of Large Language Models (LLMs) has fundamentally transformed computational linguistics, driving significant shifts in machine translation, conversational AI, and document automation [1]. Recently, generative AI has extended its influence into the domain of literary creation, encompassing forms such as novels and poetry. However, replicating the intrinsic creativity, subjectivity, and nuanced expressive elements of literature—most notably an author's distinctive writing style—remains a formidable challenge. Despite technological progress, current methodologies for modeling and imitating individual stylistic traits exhibit pronounced limitations [2]. Existing generative and corrective systems often over-prioritize grammatical and formal consistency, leading to the standardization or removal of intentional stylistic deviations. Such deviations, however, are fundamental to literary expression and artistic freedom; their erasure results in the loss of an author's unique sensibility and experimental voice. Furthermore, these systems frequently fail to capture specific stylistic intentions or account for the complex contextual structures inherent in literary works. In this study, we empirically demonstrate that training models on stylistically distinct corpora enables the partial reproduction of certain narrative features. For instance, models trained on datasets characterized by frequent polite expressions tend to mirror these tendencies in appropriate contexts. Nevertheless, quantitative assessments reveal that stylistic alignment with actual authors remains limited to approximately 20–30%. This suggests that writing style is a multi-layered construct involving narrative trajectory, implicit emotional depth, and deliberate rule-breaking—elements that extend beyond mere statistical pattern extraction [3]. Consequently, this study proposes a novel approach designed to accommodate an author's unique expressive strategies and intentional deviations, moving beyond superficial imitation. This work serves as a foundational step toward developing sophisticated, AI-driven creative assistance systems. The remainder of this paper is structured as follows: Section 2 reviews existing literature; Section 3 details the proposed methodology; Section 4 presents experimental evaluations; and Section 5 concludes with a discussion of future research directions.

2. RELATED WORK

Table 1 provides a comprehensive summary and analysis of relevant studies in the field. As the application of Large Language Models (LLMs) has expanded rapidly across diverse domains, extensive research has been conducted to enhance their adaptability and optimization. For instance, [4] systematically investigated the factors influencing fine-tuning performance by experimenting with various scaling dimensions, including model size and data composition. Their findings revealed that performance follows a multiplicative scaling law, with model size being the primary driver of improvement—a result suggesting that efficient tuning necessitates a holistic consideration of interacting variables. In the realm of personalization, [5] addressed the lack of diversity in LLM-based recommendation systems by proposing the DLCRec framework. By decomposing the recommendation process and employing stage-specific fine-tuning alongside data augmentation, they successfully enhanced diversity and personalization without compromising accuracy. Meanwhile, the pedagogical implications of LLMs were explored in [6], which compared human and LLM-based feedback in L2 writing. While LLM feedback positively impacted lexical diversity and fluency, it remained limited in capturing subtle semantic nuances and cultural contexts. Practical deployment challenges were addressed in [7], which developed a server-based 'Proofread' feature for Gboard. By utilizing reinforcement learning and inference optimization, the system effectively reduced latency for real-time mobile use. Shifting the focus to autonomous capabilities, [8] introduced the Learning Through Communication (LTC) paradigm, enabling models to collect data through environmental interaction without human supervision. Similarly, [9] examined the utility of LLMs in academic tasks, finding that while ChatGPT-assisted literature reviews were beneficial for summarization, issues such as hallucinations necessitated human oversight. Domain-specific applications have also seen significant progress. [10] employed Reinforcement Learning from Human Feedback (RLHF) to enhance empathy in psychological counseling models, though expert evaluations indicated only partial success. To better understand these emotional boundaries, [11] introduced the EmoXpt framework, revealing that LLMs tend toward consistently positive expressions, whereas humans exhibit much more complex emotional patterns. In technical fields, [12] presented InferFix, which integrates static analysis with prompt augmentation to achieve high-accuracy automated code repair in industrial environments. Finally, [13] quantitatively evaluated LLMs in academic peer review, concluding that while LLMs can perform surface-level evaluations, they struggle with deep critical reasoning, further highlighting the indispensable role of human-AI collaboration.

Table 1. Comparative Analysis of Related Work

Paper	Problem	Approach	Results	Future Work
[4]	Limited understanding of factors affecting LLM fine-tuning performance	FMT/PET-based scaling combination experiments and analysis of resource-environment factors	Fine-tuning performance follows a multiplicative scaling law; model size has the largest impact	Need combinational consideration of model size, data volume, and scaling factors for optimal fine-tuning
[5]	Lack of diversity control in LLM-based recommendation systems	DLCRec framework with three-stage recommendation	Accurate recommendation control by genre; outperforms state-of-the-art methods	Advanced user preference control, real-world deployment, and

		process and stage-wise fine-tuning		multi-platform integration
[6]	Insufficient analysis of human vs. LLM feedback effects in writing	ICNALE-based analysis of human vs. LLM feedback in L2 essays	Improved lexical diversity and fluency; LLM shows more consistent results than humans	Application to diverse writing genres and educational settings; long-term impact analysis
[7]	Input error correction limitations and poor mobile user experience	Server-based LLM correction system with RL-based tuning and inference optimization	Improved accuracy and latency; stable real-device performance	Expansion of mobile-based features, personalization, and privacy protection
[8]	Limited adaptability of LLM agents in online environments	LTC paradigm with interaction-based learning and LLM-PPO integration	ALFWorld, HotpotQA, GSM8K benchmarks show 3–13% performance gains	More communication patterns, real-time interaction, large-scale deployment, and open-sourcing
[9]	Limited multimodal emotion representation and robustness	Rule-based fusion of nonverbal signals with LLM via early fusion	93% accuracy on RAVDESS+BAUM-I; reduced robustness in cross-datasets	Multimodal expansion, explainability, and service-level application
[10]	High burden of literature review in undergraduate research	ChatGPT-based literature survey model with human-in-the-loop evaluation	Effective for topic generation and summarization; hallucination limits autonomy	Structured HITL strategies, quantitative evaluation, security and ethics
[11]	Insufficient empathy in LLM-based psychological counseling	RLHF fine-tuning of LLaMA-7B-hf using counseling dialogue data	Partial improvement; limited domain adaptation compared to rule-based systems	Safety validation, legal compliance, privacy protection, and clinical evaluation
[12]	Insufficient analysis of emotional interaction between humans and LLMs	Comparative analysis of ChatGPT responses using survey-based human evaluation	Low emotional diversity; limited expression of complex human emotions	Diverse datasets, cross-platform analysis, contextual and narrative emotion modeling
[13]	Limitations in LLM-based code bug fixing and end-to-end deployment	InferFix framework combining static analysis, prompt augmentation, and retrieval	76.8% Java accuracy, +65.5% patch expansion; effective in MS CI pipeline	Language expansion, AST-level semantics, real-time deployment, HITL evaluation

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3. METHODOLOGY

3.1. Problem Definition and Motivation

Existing LLM-based systems for creative writing and proofreading predominantly prioritize grammatical consistency, structural coherence, and formal correctness. Consequently, experimental expressions and intentional rule-breaking—elements fundamental to literary artistry—are often misidentified as errors and subjected to standardization. Core components that define a work's unique identity, such as deliberate repetition, syntactical disruption, nuanced figurative language (e.g., metaphor and symbolism), and the narrator's emotional trajectory, are frequently misinterpreted by LLMs as mere linguistic inaccuracies. This leads to a significant divergence between human authors and AI systems regarding emotional resonance, grammatical nuance, and stylistic transformation. As evidenced by the studies summarized in Table 1 and in [6], [8], and [11], the inherent pattern-recognition mechanisms of current LLMs are insufficient for capturing the complex, context-dependent expressive rules and intentional stylistic deviations that characterize individual authorship. These persistent limitations necessitate a fundamental shift in LLM-based writing support frameworks to better accommodate the creative complexity of literary texts. To address these shortcomings, we propose a refined LLM customization approach designed to meet the following criteria:

- Linguistic Profiling: The capacity to capture external stylistic characteristics, including idiosyncratic lexical choices, sentence length distributions, and syntactic structures.
- Literary Fidelity: The ability to precisely preserve and reflect an author's artistic experimentations, such as intentional inconsistencies, deliberate grammatical deviations, sophisticated metaphorical expressions, and the distinct voice of the narrator.
- Adaptive Architecture: A structural framework that enables the model to autonomously internalize and apply creative rules and stylistic biases specific to the user, genre, and context.

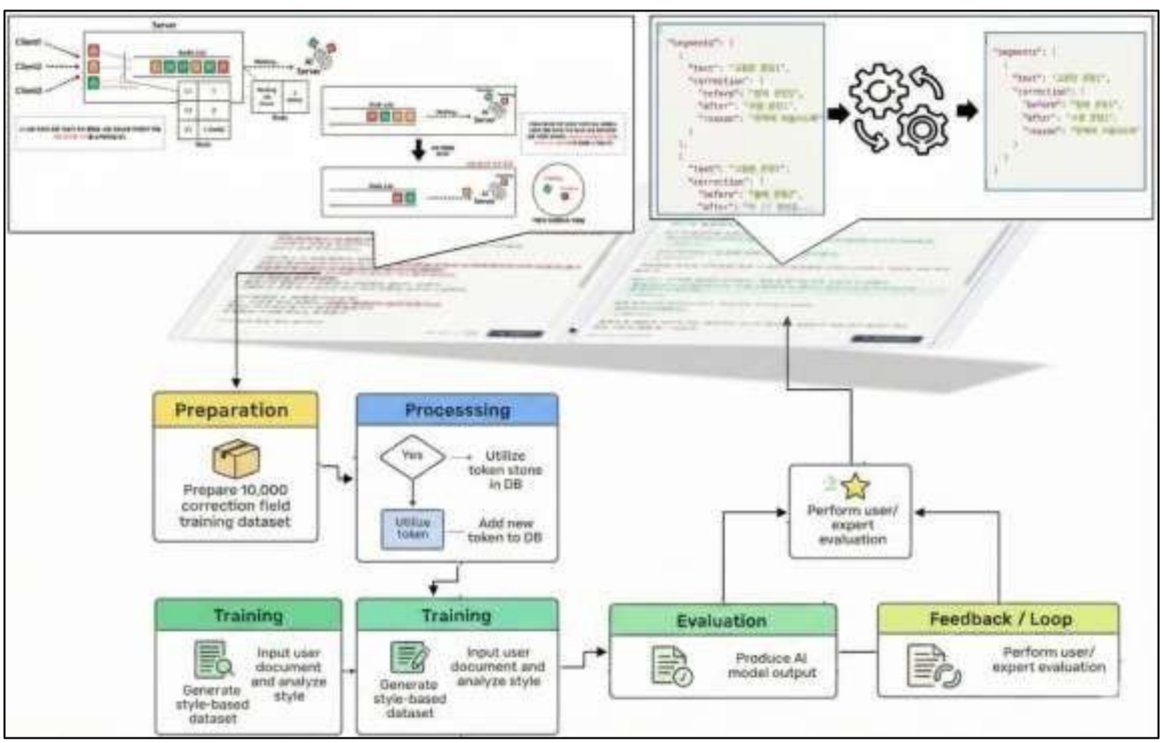

Figure 1. Procedure

3.2. A User Writing Style–Aware LLM Customization Framework

This study proposes a user writing style–based LoRA tuning pipeline that enables LLMs to more precisely reflect the stylistic characteristics and creative intentions of individual authors. The proposed pipeline consists of five stages.

(1) Construction of a Writing Style Analyzer

The writing style analyzer performs a multi-dimensional analysis of user-authored texts to extract the following stylistic features:

- Frequently used vocabulary, sentence endings, idiomatic expressions, and expression patterns
- Sentence length distributions and punctuation usage frequencies (e.g., commas, periods, quotation marks)
- Emotion-related vocabulary (positive, negative, neutral) and emotional flow patterns
- Usage of experimental literary techniques such as metaphor, symbolism, repetition, and disruption
- Patterns and frequencies of grammatical errors or intentionally broken grammar

The analyzer is engineered through a hybrid architecture that integrates traditional rule-based methodologies with transformer-based style embeddings and feature classifiers. This dual approach facilitates the quantitative extraction of both surface-level metrics—such as lexical variety and average sentence length—and profound stylistic idiosyncrasies, including emotional word distributions, repetitive patterns, and deliberate structural disruptions. By functioning as a core component of the data engineering pipeline, this stage ensures that experimental stylistic nuances are meaningfully encoded for model training and preservation. The style recognition module specifically targets an author's lexical preferences, syntactic constructions, and expressive tendencies, maintaining stylistic integrity throughout subsequent proofreading and analysis phases. Furthermore, the correction exception module evolves beyond static database lookups by implementing sophisticated pattern recognition and context-aware filtering. This includes genre-specific classification—distinguishing between conversational dialogue, formal narration, and experimental poetic structures—which allows for the application of composite exception logic instead of rigid, deterministic correction rules. Stylistic feature extraction is executed via a proprietary hybrid algorithm that operates concurrently across multiple granularities, spanning the sentence, paragraph, and document levels. This multi-level analysis ensures a holistic capture of the author's stylistic fingerprint, providing a robust foundation for personalized model adaptation.

(2) Style-Based Dataset Construction

The fine-tuning dataset is constructed around sentence-level error cases and their corrected counterparts across five categories: grammatical errors, spelling errors, stylistic inconsistencies, intentional coherence breakdowns, and readability improvements. Using the style analyzer, author-specific stylistic features are extracted and transformed into prompt-based representations that are incorporated into model inputs.

Based on the extracted stylistic features:

- Personalized sentence–correction pair datasets are generated. For example, for authors who frequently employ polite speech, neutral-style sentences are automatically transformed into polite-style correction pairs.
- Sentences containing intentional deviations (e.g., metaphor, repetition, grammatical disruption) are labeled as "correction exceptions," encouraging the model to preserve them rather than normalize them. Diverse experimental styles and creative expressions are deliberately included in the dataset, enabling the model to learn such instances as creative choices rather than errors.

(3) Personalized LoRA-Based Lightweight Fine-Tuning

Based on the analysis and dataset construction:

- A Google Gemma 3 4B–based LLM is fine-tuned using the Unsloth LoRA technique on a per-user basis.

- The objective is to softly inject an author's stylistic biases and experimental expression habits directly into the model parameters.

By leveraging LoRA-based tuning, the proposed approach minimizes computational and data requirements while enabling rapid deployment of personalized LLMs tailored to individual authors.

(4) Exception Handling Rules for Experimental Style Disruption

During the model's proofreading stage:

- Expressions that appear grammatically incorrect but clearly convey creative intent within context are preserved rather than corrected.
- Predefined experimental expression patterns (e.g., metaphor, disruption, repetition) are registered in a correction exception database.
- The correction algorithm continuously cross-references this database in real time, and matched expressions are retained in their original form without modification.

(5) Evaluation Methodology and Performance Validation

To overcome the limitations of existing evaluation approaches (e.g., [6], [11]), which primarily focus on accuracy or grammatical correctness, this study adopts a multi-faceted evaluation framework:

- Style Similarity Score: Measures the degree to which model-generated text aligns with the original author's style using deep learning–based style embeddings.
- Intentional Coherence Breakdown Preservation Rate: Quantifies how effectively experimental stylistic elements are preserved in generated outputs.
- User-Based Style Satisfaction: Evaluations by authors, critics, and general readers assessing creativity, authorial identity, and overall satisfaction (e.g., on a five-point Likert scale).
- Additional Metrics: Traditional metrics such as Perplexity, BLEU, and ROUGE, combined with human-in-the-loop qualitative evaluations.

This comprehensive evaluation framework is essential for empirically demonstrating the extent to which an LLM can preserve and extend an author's individuality, creativity, and experimental expression.

4. Implementation and Evaluation

The proposed platform is structured into a hierarchical four-layer architecture, comprising an

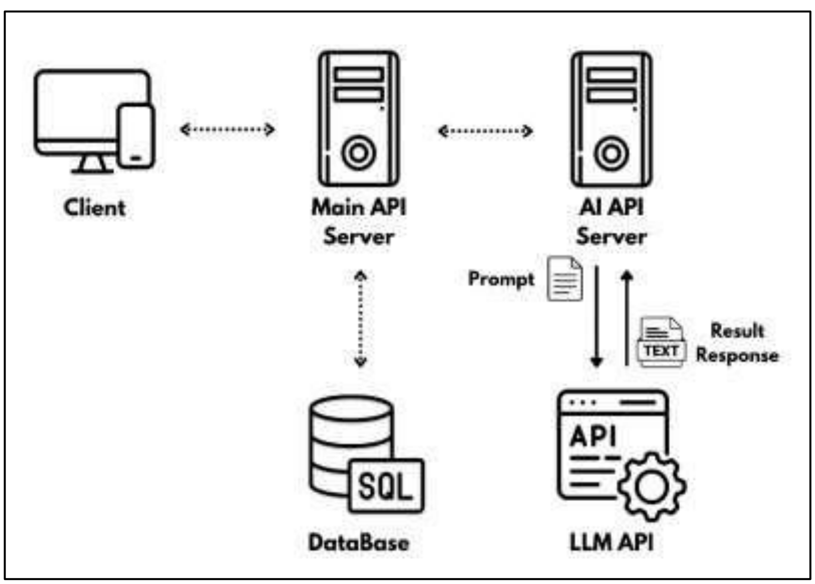

Figure 2. Four-layer architecture

application layer, a user request processing layer, an LLM processing layer, and a data layer. Users interact with the platform via a web-based interface, from which input text is routed through the request processing layer to both the primary application server and the dedicated LLM server. Within the LLM processing layer, user inputs are transformed into optimized prompt-based representations. Subsequently, a fine-tuned Gemma 3 model is invoked to generate outputs that adhere to the identified stylistic constraints. These results are then transmitted back to the primary server and delivered to the user through the application layer. The data layer is specifically designed to compartmentalize user-specific stylistic profiles and longitudinal proofreading histories. This separation ensures consistent, style-aware support during recurrent user interactions, effectively facilitating personalized creative assistance by maintaining stylistic continuity across multiple sessions.

Table 2. Comparative Analysis of Creative LLM Research

Reference	Future Research Direction	Experimental Style Included (Metaphor, Disruption)	Real Creator / Expert Feedback	Multi-tasking & Literary Expression Preservation
[4]	Combinational consideration of model size and data scaling		O	O
[5]	Advanced user preference control and real-world service deployment		O	
[6]	Application to diverse writing genres and educational settings	O		○
[7]	Feedback-driven personalization, feature expansion, and privacy enhancement	O	O	O
[8]	Expansion of communication patterns and large-scale domain learning			O
[9]	Multimodal emotion fusion and robustness improvement			O
[10]	Human-in-the-loop strategy design and ethical safeguards		O	
[11]	Safe deployment, legal compliance, and clinical validation		O	
[12]	Large-scale diverse datasets and contextual emotion modeling			O
[13]	Language expansion, AST-level semantics, and HITL validation		O	

Drawing upon the methodology in [9], the integration of non-verbal modalities—such as kinesis and physiological signals—offers a promising extension for the proposed multitasking and literary expression detection modules. For instance, when the system generates storyboards or conceptual illustrations, a multimodal fusion approach could capture deeper literary contexts by synthesizing textual data with non-verbal cues like facial expressions and gestures. Furthermore, as suggested by [11], the inclusion of experimental styles, metaphors, and intentional disruptions in the dataset must be balanced with rigorous legal and ethical labeling. By tagging potentially sensitive or harmful expressions, explicit correction-exception criteria can be established, ensuring both creative freedom and safety. The reliability of real-world creative assistance can be further bolstered through iterative feedback from authors and readers, alongside clinically grounded validation in collaboration with domain experts. In terms of data engineering, [13] indicates that labeling processes incorporating linguistic diversity and Abstract Syntax Tree (AST)-level semantic information can significantly enhance expressive variety. Finally, integrating human-in-the-loop (HITL) validation strategies directly into the fine-tuning loops—driven by real-time feedback from professional authors—will further strengthen the adaptability and scholarly credibility of the proposed framework.

5. CONCLUSION

This study empirically demonstrates the potential of Artificial Intelligence as a creative collaborator that transcends mere stylistic imitation to embrace an author's unique individuality and experimental spirit. By integrating continuous feedback through real-time user interactions, the proposed framework addresses a fundamental void in existing AI-based writing systems: the inability to preserve the creative and expressive freedom inherent in literary works. To this end, we developed an LLM-based creative assistance platform tailored to the Korean literary environment and verified that fine-tuning enables the model to reflect an author's stylistic intent with significant fidelity. Notably, experimental evaluations using the works of a professional novelist as training data revealed that the model's outputs aligned with the author's intended expressions at an approximate agreement rate of 80%. A key contribution of this research is the deliberate inclusion of 'coherence breakdowns'—intentional violations of stylistic and linguistic norms—within the training dataset. This approach enables the model to recognize such deviations not as errors, but as legitimate creative techniques, thereby treating them as artistic elements rather than targets for correction. The proposed platform systematically categorizes correction criteria into five distinct domains: grammar, spelling, readability, writing style, and coherence, with dedicated datasets optimized for each. Currently, the writing style recognition and grammatical correction modules serve as the system's core components. Future research will expand this platform by developing advanced modules to support narrative foreshadowing, analyze character development trajectories, and predict reader responses for evaluative insights.

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