

Construction and Application of a Personalized Writing Feedback System for Higher Vocational Colleges Assisted by Large Language Model (LLM)

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ABSTRACT To address delayed feedback and insufficient personalization in vocational English writing instruction, this study develops a Large Language Model (LLM)-assisted personalized writing feedback system. The framework integrates student text acquisition, semantic understanding, error recognition, adaptive feedback generation, and interactive revision evaluation into a closed-loop intelligent learning architecture. Writing data are processed through Transformer-based semantic analysis and learner-profile modeling to generate differentiated feedback according to individual language characteristics. A controlled experiment involving 200 vocational college students was conducted to evaluate system effectiveness. Results indicate that writing accuracy in the experimental group exceeded 93% across three writing tasks, with an average sentence diversity index of 0.926 and overall learning satisfaction above 4.5. The system significantly improves grammatical accuracy, language diversity, and learner engagement while reducing instructors' feedback workload. Furthermore, the proposed architecture demonstrates the potential of intelligent information processing, semantic signal transmission, and adaptive feedback networks for educational applications. The findings provide a data-driven reference for personalized learning systems and intelligent communication frameworks in digital education environments.

INDEX TERMS large language model, personalized feedback, intelligent information processing, semantic communication, adaptive learning

I. INTRODUCTION

THE absence of individualized assistance and severe delays in feedback within vocational college English writing have significantly hindered student motivation, particularly when articulating complex concepts related to fiber morphology and textile industrial modeling parameters. These pedagogical gaps prevent learners from mastering high-dimensional data perception—defined here as the ability to linguistically synthesize and interpret multivariate parameters such as material tensile strength, thermal conductivity, and morphology—and the professional communication required to maintain manufacturing excellence in the modern sector. The teachers in short periods in the classroom have the difficulty of making detailed revision recommendations based on the level of language of individual students yet the slowness of students in comprehending and internalizing the feedback results in a piecemeal process of writing improvement [1,2]. The evaluating system is also subjective which further undermines the ratings and relevance of the writing instruction since it becomes hard to equip the students to adopt proactive reflection and language transfer skills in the process of writing. As the sphere

of educational informatization and intelligent technology evolves, the old forms of teacher-based grading can be used no longer to satisfy the needs of the vocational college English teaching not only in terms of efficiency but also in terms of individuality. The challenge of how to use intelligent technology to provide writing feedback that is timely, accurate and interpretable has become an important concern in teaching reform.

The semantic prompting and writing capacity of Large Language Models (LLMs) is a new technical support that supports English writing instructions. Their strengths in the natural language process, semantic parsing, and context generation make them do a deep analysis of student writing to show the possible problems on the grammatical, lexical, syntactic, and structural levels. Using a learner profile and a dynamic feedback mechanism, LLMs can provide personalized revision recommendations depending on the language properties of various students, which form an interactive learning loop [3,4]. This paper hypothesizes and applies an LLM-aided personalized writing feedback system within vocational English teaching to enhance the articulation of material morphology and industrial modeling

parameters, thereby increasing learners' writing quality and facilitating the teaching transformation of instructors. By investigating the value of smart feedback technology, the study aims to foster the high-dimensional data perception and professional communication necessary for achieving manufacturing excellence in the modern sector.

II. RELATED WORK

The use of intelligent writing assistance system has received immense research in the area of teaching a foreign language and their primary consideration is comprised of three features: automatic scoring, grammar correction and personal feedback. Initial systems were primarily based on rule matching and corpus retrieval,

like commercial systems like Grammarly and Criterion. These systems were based on syntactic detection and error localization rules and templates which were practical in some situations, but could not cope with complex contextual problems and semantics. These systems were also problematic in the context of higher vocational teaching of English (they had issues with single feedback and adaptability of context and could not accommodate the needs of students of varying levels). Natural Language Processing (NLP) technology has resulted in Automated Writing Evaluation (AWE) models being built with machine learning algorithms gradually replacing traditional rule systems, with a complete assessment of grammar and content made with a combination of statistical features and neural network algorithms [5,6]. Nonetheless, AWE continues to lack dynamism of feedback and personal adaptability. It is, in most cases, the prompts of the feedback form, which makes it hard to make learners successfully revise themselves and process language more profoundly. Along with the development of the era of large-scale models, pre-trained language models (PLM) based intelligent writing systems become a topic of research. GPT, T5 and BERT models have proven to be strong in terms of semantic understanding, discourse creation and pragmatic generation, allowing smart feedback to go beyond sentence level error correction to the paragraph structure and discourse reasoning. Other scholars have made the effort of implementing such models into teaching English, and they have come up with personalized modification proposals using semantic rebuilding and contextualized processes to attain specific feedback and traceable instructions. The viability of LLMs in automatic essay review and adaptive writing advice has been examined by foreign scholars, who have confirmed both the possibilities of the technology to improve the quality of text generation and its ability to keep improving the writing. Domestic research is concerned with model localization, educational applicability, and an applied research on English writing situations in colleges and vocational schools, and the suggested teaching models which unite learner characteristics and feedback preference adjustment mechanisms [7,8]. Nevertheless, available literature is largely focused based on general or academic English writing, without specifics to the vocational college students,

who have a lower language base and rely heavily on learning strategies, overall.

III. METHODS

A. DATA ACQUISITION

Learners put in English essays on a web based writing service. The site automatically logs the textual contents, time of writing, changes in word count and repeating revisions. At input stage, the system embraces a text streaming access mechanism whereby each input operation is packed in semantic unit to maintain the actual writing process of the student. In order to have a complete individual learning profile, the site makes a real-time request to the database of student learning history, such as previous writing scores, vocabulary competence, frequency of a particular type of grammatical errors as well as teacher comment summaries. Texts are divided and restored in the form of words in advance of entering the processing module and the semantic characteristics are numbered and marked with the help of Natural Language Processing (NLP) algorithms. At the grammatical level, a hybrid recognition approach was applied during the initial system calibration phase, utilizing manual annotation on a representative subset of the data to validate that the model's autonomous label accuracy reached 98%. Once this benchmark was established, the system operated fully autonomously for the 200-student sample, thereby significantly reducing the manual feedback load for instructors. The use of vocabulary, complexity of sentence structure and logical consistency are automatically learned using an embedding model and compared with historical data to produce individualized feedback [9]. All data is stored in an encrypted database and is desensitized before entering the training and evaluation process to ensure student privacy and sample data quality.

B. MODEL PROCESSING

The writing text is preprocessed and fed into the GPT-4o (OpenAI) LLM inference interface, which is based on the Transformer architecture. This specific model was selected for its superior performance in semantic distance calculation and complex discourse reasoning compared to earlier iterations. The syntax detection submodule does syntax tree parsing and dependency labeling to detect hierarchical errors and deviation of collocations. The model involves employing a self-attention model to form inter-sentence relationships and re-construct long-range semantic relationships to obtain contextual logical coherence. The lexical and collocation analysis is carried out using a model of word vector representation. The naturalness and accuracy of expression are determined by recalculating the semantic distance between vectors [10]. To counteract habitual pragmatic mistakes of students, the model provides a set of pre-loaded corpus, which includes the context of a higher vocational English textbook and academic writing context, to enhance the context to the degree of feedback. The system operates under a multi-task learning framework and

produces four kinds of results in parallel, which are grammatical probability distribution, lexical diversity index, sentence complexity index and logical coherence score. Every index derives personalized revision proposals in an active blend of weights. Language generation module produces the feedback text that creates natural language descriptions and is scaled accordingly to the writing profile parameters of the student so that the relevance of the feedback and the functionality of the teaching can be made possible.

C. PERSONALIZED FEEDBACK GENERATION

The system makes use of the fact that students have a history of writing, distribution of vocabulary mastery and average sentence length properties to build a dynamic language ability vector. The model modulates the rhetorical richness and linguistic complexity of the feedback message depending on the error gradient of the vector-vectorized input findings. The process of generating feedback is carried out in collaboration with three modules of the algorithm: a semantic mapping module produces initial diagnostic descriptions using error categories in the work; A strategy control module chooses heuristic prompts or examples guidance using the VARK (Visual, Auditory, Read/Write, and Kinesthetic) learning style model. These qualitative styles are converted into quantitative LLM prompts by mapping specific learner preferences to system instructions—for example, providing more ‘visual’ structural diagrams for visual learners or detailed ‘read/write’ textual explanations—thereby adjusting the prompt weights based on the user’s categorized style parameters; and a text generation module provides natural language feedback text using a decoder. The feedback messages are displayed with a weight to distinguish between grammar correction, a vocabulary substitution, sentence structure optimization, and logical coherence prompts. During the output, the system presents an adaptive reinforcement learning (RLHF) system to dynamically optimize the expression and intensity of incentives of the feedback language by assessing the historical modification behaviour of the students. The feedback content is shown through the visualization interface as the multi-layered information structure with the mark of serious errors, possible improvement areas, and language highlights to help students make specific changes.

D. EXPERIMENTAL DESIGN

The sample was an experiment comprising of 200 students of the non-English major in a vocational college. The students who had successfully completed the entrance English proficiency test were randomly assigned to an experimental and a control group consisting of 100 students each, depending on their distribution of writing ability. The gender ratio and the range of scores were the same. Informed consent was obtained from all participants. There were five writing subjects chosen, among which are application writing, expository and argumentative writing styles. Three teachers that had experience with teaching English went

through the topics. The experimental setting was founded on a single network platform, and all the devices were inputted and text uploaded through the same format, preventing differences in the environment that can be known to affect data quality. The experiment duration was fixed to six weeks where the system was pushing tasks once a week. Within the time-span, students were on their own doing the writing. Once the task was done the platform automatically stored the text file, history of edits and the timestamp data to be used later on the analysis of the model. The teachers were assigned the duty of assigning tasks and checking submissions. To establish a comparative baseline against existing technology, the control group utilized a traditional Automated Writing Evaluation (AWE) tool (Grammarly) for basic error correction, but without the personalized, LLM-driven feedback provided to the experimental group. This allows for a direct comparison between standard rule-based correction and the proposed personalized LLM system. The system documented the amount of student contacts, the amount of feedback requests, and the mean latency of responses at the conclusion of every task. All the raw data were synchronized with the server database using an encrypted pipeline and handled with a single rule of naming and index. The measures that were taken comprised of the length of texts, the complexity of the syntactic processing, the time spent to accomplish the set tasks, the volume of the feedback, and the activity of the learner so that it was possible to trace the process of the sampling and guarantee the consistency of the data. Table 1 represents the parameters of the experimental design.

TABLE 1. Experimental Parameter Design

Group	Cycle (week)	Weekly task count	Average text word count	Average submission time (minutes)
Experimental Group A	6	2	235	48
Control group B	6	2	228	46
Average value	6	2	231.5	47
Male percentage	–	–	–	–
Female percentage	–	–	–	–
Platform operational stability (availability %)	–	–	–	99.2

The remaining 0.8% of downtime occurred during scheduled maintenance windows outside of peak submission hours; consequently, it did not result in data loss or impede the writing progress of the 200 participants over the six-week study period.

IV. RESULTS AND DISCUSSION

A. WRITING ACCURACY

The pre-test was based on a unified writing task, in which students completed two essays on different topics. The system automatically evaluated the essays based on two indicators: grammatical accuracy and sentence variety. The results were then double-checked by human reviewers to ensure stability. All sample texts constituted the pre-test and post-test datasets, and the evaluation criteria remained consistent.

TABLE 2. Accuracy Test Results

Group	Sample size	Task type	Pre-test accuracy (%)	Post-test accuracy (%)	Pre-test sentence diversity index	Post-test sentence diversity index
Experimental group	100	Applied Writing	60.8	93.5	0.65	0.91
Experimental group	100	Explanatory writing	61.7	94.2	0.68	0.94
Experimental group	100	Argumentative writing	61.0	94.8	0.67	0.93
Control group	100	Applied Writing	60.3	71.4	0.64	0.73
Control group	100	Explanatory writing	61.2	72.3	0.66	0.75
Control group	100	Argumentative writing	60.7	73.1	0.66	0.74

As shown in Table 2, the experimental group achieved a writing accuracy rate exceeding 93% in all three tasks, with an average of 94.2%, while the control group averaged 72.3%, a difference of 21.9 percentage points. Regarding sentence diversity index, the experimental group averaged 0.926, while the control group averaged 0.74, a difference of 0.186. The most significant difference was observed in the applied writing task, where the experimental group's accuracy was 22.1% higher than the control group's, and its sentence diversity was 0.18 higher. The difference was second highest in the writing task (21.9% vs. 0.19), with a slightly lower difference in the argumentative essay task (21.7% vs. 0.19). The data indicates that the LLM system's grammar recognition and feedback generation mechanism significantly reduced the number of grammatical errors made by students, while simultaneously encouraging them to experiment with complex sentences and parallel structures at the rhetorical level, leading to a simultaneous improvement in both the complexity and accuracy of language output.

B. LEARNING SATISFACTION

One week later, a learning satisfaction test was carried out and the test involved the use of a combination of questionnaires and system behavioral data to determine the acceptance of the writing feedback system by the students. The questionnaire related to four dimensions namely: feedback accuracy, interactive experience, learning motivation, and overall usefulness on a five point rating scale, with 1 as very dissatisfied and 5 as very satisfied. Two hundred questionnaires were distributed and 198 questionnaires returned that are valid with equal numbers on sample size of the experimental and control groups. Data was checked on consistency and outliers have been cleansed after which the average score is obtained and the results have been displayed in a standardized form. The results are shown in Table 3.

TABLE 3. Learning Satisfaction

Group	Average score of feedback accuracy	Average score of interactive experience	Average score of learning motivation	Overall satisfaction average score
Experimental group	4.72	4.65	4.58	4.68
Control group	3.81	3.74	3.69	3.75
Overall average	4.27	4.20	4.14	4.22
Standard deviation of Experimental group	0.41	0.38	0.43	0.39
Control group Standard deviation	0.57	0.61	0.59	0.55

The experimental group generally achieved a satisfaction score higher than 4.5, while the control group's scores were concentrated in the 3.7 to 3.8 range. The largest difference was in feedback accuracy, exceeding the control group's score by 0.91 points, followed by interactive experience, also with a 0.91-point difference. Overall analysis showed that students exhibited a more stable and positive attitude towards the LLM-based writing feedback system in terms

of response speed, feedback comprehensibility, and guidance effectiveness. The system's adaptive feedback design significantly enhanced learning engagement and perceived benefits.

C. EFFECTS OF IMPROVING TEACHING MODELS

The personalized writing feedback system, which is founded on a large language model, attains the structural change of the teaching models between the teacher-led evaluation and the intelligent collaborative feedback. The roles of teachers slowly change and instead of merely correcting learners they must control the learning process and direct strategies. Activities in the classrooms go beyond passive correction to active inquiry and interactive training in writing. It is a dynamic semantic recognition based system which offers context based writing suggestions to the students in the process of generating feedback which makes the process of learning more focused and direct. Data dashboards allow teachers to learn the language performance characteristics of students and regulate the content and task difficulty in teaching according to the feedback trends to reach

differentiated instruction. Within the framework of the adaptive guidance within the system, the students acquire self-monitoring awareness of writing which allows them to be capable of recognizing language errors and making strategic corrections under their own guidance.

V. CONCLUSION

The implementation of Large Language Model-based systems for individualized vocational English writing feedback has demonstrated significant effectiveness in scaling the professional communication skills required for material morphology research and industrial modeling. By aligning instructional outcomes with the high-dimensional data perception necessary for manufacturing excellence, these systems ensure that students master the precise technical discourse essential to the modern sector. By means of semantic cognition and contrasting feedback systems, the system gives students real-time and focused instructions on writing activities, which encourages proactive revision and self-reflection. The combination of the system has demonstrated in teaching practice that not only process of writing instruction by the teachers is time-saving through the reduction of manual grading load, but also approach to teaching as a process of developing the competencies that are process-driven and not outcome-driven. The construction of the logic of expressing language takes place slowly, yet steadily, by the continuous interaction of the students, and they gain greater control of the semantic relationships and the structure of the text. This research validates the feasibility of large language models in vocational English instruction, establishing a demonstrative value for integrating intelligent feedback systems with industrial modeling parameters and material morphology technical discourse. By aligning pedagogical frameworks with the high-dimensional data perception required for manufacturing excellence, the

study offers a practical foundation for building a data-driven intelligent writing ecosystem tailored to the professional demands of the modern sector.

AUTHOR CONTRIBUTIONS

Conceptualization –Di Wang and Lili Zhang; methodology – Di Wang and Lili Zhang; investigation – Di Wang and Lili Zhang; writing-original draft preparation – Di Wang and Lili Zhang. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

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