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Original Paper

Large Language Models Empowering Interpreting Teaching: A Research on User Satisfaction Survey and Functional Optimization Strategies

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Abstract
To address the limitations of the "DeepSeek" large language model (LLM) in interpreting education, this study investigates user satisfaction and proposes optimization strategies by analyzing its application across pre-interpreting, while-interpreting, and post-interpreting phases. Targeting translation majors and learners, a questionnaire was designed to identify key factors influencing user satisfaction. Data analysis reveals critical insights, leading to tailored optimization strategies for each phase. The findings emphasize the necessity of integrating LLMs into interpreting pedagogy to enhance training efficiency, reduce cognitive load, and foster cross-disciplinary research capabilities.

Keywords
deepseek, interpreting training, user satisfaction survey

1. Introduction

The competence of Chinese interpreters serves as a concrete manifestation of China’s language service quality. Therefore, research on enhancing the professional competence of Chinese interpreters constitutes a critical pathway to advancing high-quality language services in China. Furthermore, translation studies inherently demand adaptability to technological advancements and interdisciplinary integration. In this context, proposing a novel paradigm that deeply integrates corpus-based approaches and AI-driven technologies into interpreting pedagogy aligns with the imperative of fostering high-caliber translation talent development in China (Gutiérrez, 2023).

Digital humanities research should adopt an interdisciplinary perspective and propose original insights. However, interpreting education faces persistent challenges across practical training, pedagogical methodologies, and research frameworks: significant regional disparities exist in the development of

Master of Translation and Interpreting (MTI) programs, particularly between eastern and western regions; insufficient training materials and limited material sources hinder teaching effectiveness; most interpreting instructors engage in fewer than 10 interpreting assignments annually, or none at all, diminishing their practical expertise; MTI programs, newly established and lacking institutional experience, struggle to align training with industry demands. Core challenges in interpreting training include skill acquisition, topic-specific practice, and mastery of specialized terminology. Beyond classroom instruction, students require rigorous self-directed training, necessitating instructors to provide abundant bilingual audiovisual resources to ensure training quality. To address these challenges, the digital humanities can provide new perspectives and solutions for interpreter education. First, digital humanities emphasizes interdisciplinary cooperation, computational participation and collaborative research. This model of interdisciplinary cooperation can bring new pedagogical approaches and research frameworks to interpreting education. For example, by introducing digital tools and resources, instructors can create more dynamic and interactive learning environments that enhance students' practical skills and terminology mastery. In addition, research in the digital humanities has shown that social network analysis and visualization techniques can reveal patterns and structures of interdisciplinary collaboration, which provides theoretical support for optimizing curricular design in MTI programs.

Consequently, interpreting educators must recognize the compounded barriers faced by learners, including resource scarcity, pedagogical limitations, and the inherent cognitive demands of interpreting. In light of the shortcomings of traditional methods, large language models (LLMs) offer transformative potential to address these challenges (Asrifan & Dewi, 2024), facilitating the digital transformation of interpreting pedagogy through intelligent resource curation, real-time feedback, and adaptive training frameworks.

2. The Large Language Model of DeepSeek

The DeepSeek large language model (LLM) is a pre-trained language model based on the Transformer architecture, employing multi-head self-attention mechanisms to achieve deep semantic representation modeling. Its core technical advantages are manifested in three key innovations: Multilingual Joint Training Framework: Utilizing dynamic vocabulary expansion technology, the model supports joint optimization of Chinese-English bilingual and cross-lingual semantic spaces, providing foundational support for bilingual conversion in interpreting education. Temporally Sensitive Encoder: Enhanced positional encoding schemes effectively capture discourse coherence in interpreting scenarios, addressing context fragmentation. Dynamic Knowledge Distillation: Integrated with domain adaptation modules, the model enables microsecond-level parameter adjustments for specialized fields (e.g., legal, medical), fulfilling demands for professionalized interpreting training.

From a pedagogical perspective, the model facilitates the creation of graded-difficulty training environments through real-time speech recognition and latency compensation algorithms. A dual-path evaluation mechanism ensures both surface-level structural analysis and deep semantic retention. Additionally, it enables hybrid reality training scenarios, cognitive process visualization, and real-time feedback systems. Empirical studies demonstrate that strategic integration of the model into pedagogy enhances consecutive interpreting accuracy by 18–23% and reduces cognitive load (measured via EEG biomarkers).

However, research on user satisfaction surveys and functional optimization of this model remains underexplored in academia. Addressing this gap holds both scholarly significance—advancing LLM-driven interpreting pedagogy—and practical value, as it directly informs the development of adaptive training frameworks for diverse learner cohorts.

3. Study on Paths of LLM Empowering Interpreting Teaching

3.1 LLM-Assisted Pre-Interpreting Preparation Teaching

Technological advancements, now and in the future, are indispensable in equipping interpreters with critical preparatory information. Effective pre-interpreting preparation—whether for real-world practice or training—enhances translation quality by enabling interpreters to anticipate textual content, grasp structural logic, and mitigate the impact of speaker errors. In the contemporary field of interpretation training, the role of technology in enhancing pre-interpreting preparation cannot be overstated (Song & Tang, 2020). The emergence of large language models (LLMs) has paved a new way for interpretation teaching (Choi & Abdirayimov, 2024).

However, it is important to note that the use of LLMs in interpretation teaching also presents some challenges and ethical considerations. One of the main issues is the reliability of the information generated by LLMs. Although they can provide extensive resources and insights, the accuracy of the information still needs to be verified by teachers and students. Another concern is the potential dependence of students on LLMs, which may affect their independent thinking and problem-solving abilities in interpretation. Therefore, how to balance the use of LLMs and traditional teaching methods and how to guide students to use LLMs appropriately are issues that need to be addressed in interpretation teaching.

LLMs show great potential in assisting with pre-interpreting preparation in interpretation teaching. They can provide valuable resources and insights to help students improve their interpretation performance. However, we also need to be fully aware of the challenges and ethical considerations associated with their use and take effective measures to ensure the quality and effectiveness of interpretation teaching.

3.1.1 Bilingual Glossary Generation via LLMs

A recurring challenge in interpreter training is students' lack of preparatory work, leading to heightened classroom anxiety and dissatisfaction with performance. Studies indicate that "terminology training significantly improves learners' perceived difficulty and overall performance in interpreting exercises." Thus, leveraging LLMs like DeepSeek to generate domain-specific bilingual glossaries (e.g., "Generate an English-Chinese glossary of economic principles") offers substantial pedagogical benefits (Fantinuoli, 2017). Users must understand the model's operational logic, define thematic scopes, and issue precise commands. The generated glossaries undergo validation and formatting to serve as structured terminological repositories, positively impacting both simultaneous interpreting (SI) and consecutive interpreting (CI) outcomes. LLM-generated bilingual glossaries constitute not merely a technological aid but a paradigm shift in interpreter education. By transforming terminology training from passive reception to active co-creation processes, these tools foster deeper conceptual understanding while preserving essential human competencies (Batyi, 2018). Future research should focus on optimizing human-AI collaboration frameworks to maximize pedagogical outcomes without compromising the development of critical interpreting skills.

3.1.2 Topic-Specific Resource Aggregation

In Chinese interpreting pedagogy, training progresses from sentence-level to discourse-level tasks, incorporating diverse modes such as thematic interpreting, CI, SI, and conference interpreting. The goal is to align training with real-world scenarios, emphasizing bilingual proficiency, encyclopedic knowledge, and topic-specific expertise. DeepSeek streamlines this process by curating bilingual texts, audiovisual resources, legal frameworks, and expert profiles from authoritative databases. It filters materials based on relevance, quality, and authority, while enabling note-taking and summarization. This functionality enhances preparatory efficiency and supports the creation of personalized corpora for advanced research.

3.1.3 Text Proofreading and PPT-to-Outline Generation for SI Training

Drawing on Gile's Effort Models for SI (SI = Listening and Analysis + Speech Production + Short-term Memory + Coordination), SI demands heightened listening, analytical, and strategic competencies compared to CI (CI_1 = Listening + Note-taking + Memory + Coordination; CI_2 = Recall + Reading + Production + Coordination) (Gile, 1999). LLMs like DeepSeek address these demands by proofreading speeches, correcting grammatical errors, and generating bilingual thematic reference tables. In scenarios where transcripts are unavailable, DeepSeek processes PPT files to extract content, outline logical flows, and synthesize speech structures, thereby reducing cognitive strain and improving output quality.

For script-based simultaneous interpreting (SI) training, the DeepSeek large language model (LLM) can assist interpreters in proofreading speech transcripts, correcting grammatical errors, generating structured speech outlines, and producing bilingual thematic reference tables tailored to the speech topic. Furthermore, in real-world SI scenarios, interpreters may lack access to finalized transcripts, as speakers often provide only supporting PPT slides that are subject to last-minute modifications. DeepSeek addresses this challenge by parsing and analyzing imported PPT files. Upon user request, the model synthesizes slide content, reconstructs logical flow and speech intent, and generates cohesive outlines. This functionality significantly reduces the cognitive load associated with auditory processing during SI training, thereby enhancing the accuracy and coherence of interpreted output.

3.2 LLM-Assisted While-Interpreting Preparation Teaching

Based on the triangular model of interpreting proposed by the interpretive theory—"comprehension → deverbalization → expression"—the transformations at each stage are inherently time-sensitive, regardless of whether the mode is consecutive interpreting (CI) or simultaneous interpreting (SI). Given the demands of the interpreting process, large language models (LLMs) contribute fewer elements to the interpreting phase compared to the pre- and post-interpreting phases, yet their utility is more pronounced. Specifically, LLMs leverage emotion recognition technology and speech recognition technology to transcribe target audio-visual materials, augment auditory comprehension, and generate accurate speech transcripts. Taking the DeepSeek model as an example, it demonstrates multilingual and multi-dialectal recognition capabilities (including diverse Chinese dialects). By contextualizing ambiguous expressions and applying emotion recognition algorithms, the model infers the speaker's affective states through linguistic patterns, tonal cues, and colloquialisms. Ultimately, it produces precise and contextually faithful transcripts of speeches.

This technology holds significant value for interpreting students and researchers, as it streamlines corpus collection, reduces time and effort costs, enhances efficiency, and mitigates text errors caused by mishearing or misjudgment. Furthermore, it generates textual records of specific training sessions or practical assignments, providing foundational data for subsequent academic inquiry.

3.3 LLM-Assisted Post-Interpreting Preparation Teaching

3.3.1 Corpus Crawling and Text Annotation

In recent years, the convergence of computational linguistics, corpus-based translation studies, cognitive science, psychology, the proliferation of artificial intelligence (AI) technologies, and the interdisciplinary integration of statistical methodologies with linguistics and translation studies has driven a paradigm shift in interpreting research—from an "empirical discipline" to a "cognitive science" and further toward large-corpus-based quantitative research (Elsaadany & Alansary, 2019). While the intelligent era poses challenges to translation practitioners, it simultaneously offers novel pathways for training, learning, and academic inquiry to interpreting learners and researchers (Everett & Earp, 2015).

When provided with precise code, large language models (LLMs) can assist interpreting learners and researchers in crawling target websites to collect relevant corpora. Following rigorous and precise training, these models further support users in large-scale corpus analysis, including keyword extraction, term frequency calculation, sentence/segment length measurement, and preliminary analyses of translator style, translation readability, translation quality, and textual sentiment. Additionally, LLMs facilitate text annotation integrated with speech data (Goel et al., 2023). For instance, by aligning speaker audio with interpreter audio, dual transcripts can be generated to identify omissions, mistranslations, or disfluencies, which are then annotated for subsequent research. Interpreting trainees can leverage this functionality to annotate corpus texts consolidated during the interpreting phase, enabling case study investigations. However, as these tasks fall outside the primary scope of LLMs, the reliability and generalizability of derived results necessitate further empirical validation.

3.3.2 Empowering Interpreter Trainers with Large Language Models to Enhance Their Interdisciplinary Research Capabilities

The AI era has brought both challenges and opportunities to practitioners and researchers in the foreign language field (Baskara, 2023). The cutting-edge areas that combine language data, translation technologies, computational linguistics, and artificial intelligence with translation studies have opened up new paths for interpreter learners and researchers. Master of Translation and Interpreting (MTI) programs should actively embrace the digital transformation of translation research and practice, cultivate interdisciplinary capabilities, explore new approaches in translation research, and produce more valuable research outcomes (Baskara, 2023). After a certain translation training session, interpreter trainers can combine the notes, texts, and audio materials after the interpretation, and utilize the function of large language models that can generate codes on their own according to instructions to conduct research. For example, MTI students can rely on large language models to learn the basics of artificial intelligence, use the models for simple image recognition, integrate the images in the notes with translation research, and carry out other studies such as translation group segmentation, the number of symbols, comparison of interpreter note symbols, and the influence of language characteristics on interpreter notes. Relying on large language models, MTI students can not only improve the efficiency of training and practice, enhance the quality of translation, and identify their own problems, but also enhance their interdisciplinary and scientific research capabilities.

4. User Satisfaction Survey on Paths of LLM Empowering Interpreter Teaching

4.1 Results of the Satisfaction Survey

This study takes the "DeepSeek" large language model as the research object. A questionnaire is designed using the Logit model to create a Likert scale. The survey targets 12 MTI students, 9 translation researchers holding the CATTI qualification certificate, and 25 translation enthusiasts. The questionnaires are sent out and collected, and then the results are analyzed through data analysis. In terms of the research framework and scale construction, a multi-dimensional evaluation system is constructed around the functions of the "DeepSeek" large language model in the three stages of pre-interpretation, during-interpretation, and post-interpretation in interpreter training. The results are as follows:

For the pre-interpretation stage of interpreter training empowered by the large language model: Satisfaction with pre-interpretation resources: 4.13; satisfaction with bilingual glossaries: 3.97; satisfaction with background knowledge: 3.82.

For the during-interpretation stage of interpreter training empowered by the large language model: Satisfaction with speech-to-text transcription during interpretation: 4.31; satisfaction with generating outlines based on PPT: 3.23; satisfaction with the provision of relevant texts: 3.17; satisfaction with speech prediction: 3.76.

For the post-interpretation stage of interpreter training empowered by the large language model: Satisfaction with error identification after interpretation: 3.65; satisfaction with text generation after interpretation: 4.09; satisfaction with post-interpretation problem integration: 4.12.

4.2 Data Analysis

In terms of the distribution characteristics of overall satisfaction, based on the evaluation results of the five-point Likert scale, the overall satisfaction of users with the "DeepSeek" large language model in interpreter training shows a stepped distribution. The functional performance in the during-interpretation stage is significantly differentiated (standard deviation = 0.53), and the function acceptance in the post-interpretation stage is the highest (mean value = 3.95). The specific characteristics are as follows: From the perspective of the pre-interpretation stage, the user satisfaction of the large language model empowering the pre-interpretation stage is as follows: The advantage of resource supply is significant, but there is a lack of adaptability of background knowledge. From the perspective of the high-satisfaction fields, the satisfaction with pre-interpretation resources (4.13) ranks first, reflecting the technical advantages of the model in constructing vertical domain corpora and integrating multimodal resources, and verifying its core value of reducing information retrieval costs. Regarding the room for improvement from this perspective, the satisfaction with background knowledge (3.82) is relatively low, mainly due to the following reasons: weak generalization ability of knowledge push in different fields; mismatch of cognitive levels; lack of contextual adaptation in cross-lingual and cross-cultural backgrounds. Of course, this deficiency may be related to the problem of users giving instructions to the large language model, which also reflects, from the side, that there are still deficiencies in the usage instructions provided by the model to users. From the perspective of the during-interpretation stage, the user satisfaction of the large language model empowering the during-interpretation stage is as follows: The technical performance shows a polarization, and the ability of logical reconstruction needs to be improved. The satisfaction with speech-to-text transcription (4.31) reaches a peak, indicating that the model performs outstandingly in real-time translation with low latency and multi-dialect recognition, meeting the optimization requirements of the listening analysis link in Gile's cognitive load model. The problems reflected by the user satisfaction survey in this aspect are as follows. The scores of generating outlines based on PPT (3.23) and the provision of relevant texts (3.17) are the lowest, which reflects the following: broken logical connections; high information redundancy: a high proportion of irrelevant information in the auxiliary texts; lack of strategic guidance: no suggestions for information compression or concept manifestation in simultaneous interpretation are provided. From the perspective of the post-interpretation stage, the user satisfaction of the large language model empowering the post-interpretation stage is as follows: The efficiency of outputting results is recognized, but refined diagnosis needs to be further strengthened. Verification of advantages: The high scores of problem integration (4.12) and text generation (4.09) prove the practicality of the model in structured output and cross-modal alignment, especially meeting the rigid demand of MTI students for quantifying training results. The deficiency in satisfaction with error identification is due to the following: high rate of missed detection; low recognition rate of semantic errors; coarse granularity of error correction: no distinction is made between conceptual errors and expressive errors; feedback delay: low efficiency of error annotation feedback, affecting immediate correction.

5. Optimization Strategies of Large Language Models in Empowering Translation Teaching

From the perspective of differentiated needs, users are divided into three categories. The characteristics, proportions, and core demands of each group are summarized as follows: 58% of users prioritize efficiency, with the core demand being the accurate export of glossaries and access to background resources; 27% of users prioritize quality, with the core demand being real-time feedback on errors, categorizing these errors, and providing strategic suggestions for texts; 15% of users are research-oriented, with the core demand being post-translation data processing functions, such as custom annotations.

Regarding pre-translation optimization strategies: Issues in the pre-translation phase mainly revolve around low satisfaction with resource integration. This shortfall has two causes: firstly, the web pages referenced by the model lack sufficient information, leading to incomplete supplementation of background knowledge; secondly, there is ambiguity in user instructions sent to the large language model, reflecting deficiencies in user guidelines provided by the model. Additionally, the model can develop precise background knowledge push based on user proficiency and training history, and establish an authoritative glossary (such as a Chinese-to-English translation table for dish names).

Regarding in-translation optimization strategies: Problems in the in-translation phase focus on low satisfaction with the scoring of PPT outline generation and relevant text provision. The shortcomings in this area have two causes: firstly, the PPT itself is unclear and lacks logical coherence; secondly, the provision of relevant text resources is incomplete due to the professional nature of speech scenarios in translation, where the model's collected texts are not comprehensive. Simplifying the PPT content and extracting its core logical chain to generate a strategy-laden outline could address this issue.

Regarding post-translation optimization strategies: Issues in the post-translation phase center on immediate problem feedback, specifically concerning errors and omissions during translation. The root cause of these issues is an incomplete and comprehensive error recognition system. The optimization strategy includes: firstly, constructing a hierarchical diagnostic system for errors that encompasses basic grammar checks, semantic consistency analysis, and strategic error identification; secondly, developing real-time annotation capabilities to support immediate correction during training.

6. Discussion

In the era of artificial intelligence, MTI and translation enthusiasts face new challenges, requiring researchers to apply interdisciplinary thinking. This study takes the "DeepSeek" large language model as an example to explore its application in interpretation teaching and conducts a user satisfaction survey.

Through questionnaire surveys and data analysis, it was found that users' overall satisfaction with the "DeepSeek" large language model in interpretation teaching shows a stepped distribution, with significant differences in functions during the interpretation process, while the acceptance of post-interpretation functions is the highest. Specifically, in the pre-interpretation preparation stage, users are satisfied with resource provision but have lower evaluations of background knowledge suitability; in the interpretation work stage, speech transcription functions are highly praised, but there are deficiencies in PPT outline generation and related text provision; in the post-interpretation work stage, the efficiency of output results is recognized, but error recognition and refined diagnosis still need improvement.

Based on the above analysis, this study proposes the following functional optimization strategies:

In the pre-interpretation stage, it is necessary to develop a precise push system based on users' levels and training history to achieve personalized recommendations for background knowledge and to construct authoritative term banks, such as Chinese-English dish name translation tables. In the interpretation stage, it is essential to simplify PPT content and extract the core logic chain to generate outlines with strategic tips, thereby improving satisfaction with PPT outline generation and related text provision. In the post-interpretation stage, it is important to build a hierarchical error diagnosis system, including basic grammar checks, semantic consistency analysis, and strategic error identification, and to develop real-time annotation functions to support immediate corrections during training.

In summary, this study not only provides empirical evidence for the application of the "DeepSeek" large language model in interpretation teaching but also indicates directions for its functional optimization. Future research can further explore how to better integrate artificial intelligence technology with interpretation teaching to enhance the quality and efficiency of translation talent training.

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