Intelligent Translation System and Network Communication Optimization of Tourism English for International Tourists

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ABSTRACT This study presents an intelligent English translation system for international tourists, integrating deep learning, multimodal translation, and network communication optimization. The system addresses challenges in language recognition, cultural context handling, and low-latency transmission across heterogeneous networks. A hybrid communication framework combining offline caching, cloud collaboration, and adaptive multi-network switching ensures reliable operation under varying network conditions. Scenario-based deployment and personalized service strategies enhance usability in diverse tourism environments, while rigorous evaluation demonstrates improved translation accuracy, response speed, and user satisfaction. The approach is particularly relevant for mobile communication and electromagnetic network environments, where low-latency and robust protocol design are essential for effective real-time translation and international service interoperability. Experimental results confirm that the system supports both high-quality language services and efficient technical exchanges in global tourism and connected device networks.

INDEX TERMS intelligent translation system, network communication, electromagnetic networks, tourism English

I. INTRODUCTION

IN the context of global integration, international tourism serves as a primary avenue for promoting cultural exchange and economic development, while the global industry is a vital artery for cross-border trade and industrial collaboration. Consequently, language barriers significantly affect the travel experiences and service quality of international tourists, as well as the efficiency of technical communication within the industry's global supply chain. Manual translation, characterized by high costs, limited scope, and inadequate real-time performance, is no longer sufficient to meet the increasing demand for tourism services or rapid technical exchanges . Advances in intelligent translation technology offer novel solutions to these challenges. This study examines a comprehensive English intelligent translation system integrating deep learning, network communication optimization, and user experience design. Technical enhancements are leveraged to improve translation accuracy and response speed, providing convenient and efficient language services for both international tourists and the global industry, thereby facilitating the development of smart tourism and efficient cross-border manufacturing.

II. TECHNICAL ARCHITECTURE AND IMPLEMENTATION OF THE TOURISM ENGLISH INTELLIGENT TRANSLATION SYSTEM

A. DEEP LEARNING-DRIVEN LANGUAGE RECOGNITION TECHNOLOGY FOR TOURISM SCENARIOS

Language recognition technology in tourism scenarios forms the core foundation of intelligent translation systems, with its accuracy directly determining the overall translation quality. Deep learning employs multilayer neural network models to autonomously learn and extract linguistic features, enabling precise identification of complex language patterns. In tourism contexts, voice recognition faces challenges such as diverse accents, environmental noise, and frequent use of specialized terminology. The system integrates convolutional neural networks (CNNs) to extract local features of voice signals and recurrent neural networks (RNNs) to capture temporal dependencies [1-3].

B. CONSTRUCTION AND OPTIMIZATION OF MULTIMODAL TRANSLATION ENGINES

Multimodal translation engines are central to translation quality and user experience, incorporating various information sources such as text, voice, and images to provide faster, more accurate, and natural translation results. The translation engine utilizes a neural network model based on the Transformer framework, employing a self-attention mechanism to establish deep semantic relationships between source and target

languages. During encoding, the system processes not only textual information but also integrates speech prosodic features and visual scene data, generating richer semantic representations. Visual information guides translation decisions through a multi-stage processing pipeline: a CNN analyzes input images to identify key objects and classify scenes, while extracted text via optical character recognition (OCR) is encoded into a context vector. This vector is fed into the Transformer encoder alongside text and speech features. For example, when recognizing a restaurant menu, the context vector activates dining-related concepts, ensuring ambiguous voice inputs such as "check, please" are accurately translated in context. The decoder employs a multi-head attention mechanism to focus on different modalities, producing translation results aligned with the contextual environment [4-6].

C. TOURISM PROFESSIONAL TERMINOLOGY DATABASE AND CULTURAL CONTEXT PROCESSING MECHANISM

The tourism industry encompasses numerous specialized terms and culturally specific expressions, necessitating accurate handling to enhance translation quality. A professional terminology database is established, covering fields such as scenic spot descriptions, catering services, accommodation facilities, and transportation navigation, comprising over 100,000 tourism-related words and phrases. Organized with an ontology structure, the database facilitates semantic connections, synonym recognition, and hierarchical reasoning.

To optimize for real-time and colloquial language, the system incorporates two specialized modules:

1) Colloquialism and Fragmentation Resolver

Recognizes slang, ellipses, and common sentence fragments in rapid conversation, mapping informal expressions to semantically complete equivalents before translation.

2) Contextual Code-Switching Detection

Implements a bilingual tokenizer and language identification model to manage frequent code-switching, ensuring appropriate routing of English and non-English segments. The cultural context processing mechanism employs deep semantic analysis to identify metaphors, idioms, and expressions of politeness or deference, adapting translations according to the cultural background of the target language. A cultural knowledge map stores habits, etiquette, and taboos of various regions, dynamically integrating these rules into the translation workflow by adjusting politeness levels, detecting potential cultural conflicts, and flagging taboo terms to prevent inappropriate translations [7-9].

III. KEY TECHNOLOGIES IN NETWORK COMMUNICATION OPTIMIZATION FOR TRANSLATION SYSTEMS

A. NETWORK TRANSMISSION OPTIMIZATION FOR LOW-LATENCY REAL-TIME TRANSLATION

Real-time translation demands extremely low latency in network transmission, directly influencing user experience and system usability. The network transmission optimization strategy operates at the protocol level, utilizing a custom application-layer protocol (ALP) built on UDP to minimize latency while ensuring data integrity. Reliability is selectively implemented through an application-layer selective repeat (ARQ) mechanism to address packet loss. This custom protocol is preferred over higher-overhead standards such as WebRTC, which introduce complexity and increased latency unsuitable for resource-constrained, speech-only translation devices.

Selective reliability retransmits only critical speech data segments, minimizing overhead compared to TCP. Minimal congestion control is achieved via a loss-based rate adaptation mechanism, adjusting transmission rates based on explicit packet loss feedback. NAT traversal relies on pre-configured STUN/TURN services at the edge, simplifying the protocol stack and expediting session establishment.

The system employs an adaptive bitrate control mechanism that dynamically adjusts audio encoding parameters in real time in response to variations in network bandwidth, thereby ensuring a minimum level of communication quality under fluctuating network conditions. Rate adaptation is triggered through continuous monitoring of three key metrics: Packet Loss Rate (PLR), Round-Trip Time (RTT), and available bandwidth. To reliably estimate available bandwidth in a real-time, low-latency UDP environment, the system adopts a refined packet pair dispersion technique combined with an active probing mechanism. Specifically, sequences of closely spaced probe packets are periodically transmitted from the client device to the nearest edge node. The inter-arrival time of these packets at the receiver is measured and translated into an estimate of the bottleneck bandwidth. This passive estimation is further augmented by actively monitoring the ingress queue delays at the edge node via explicit feedback signals, ensuring that the estimated available bandwidth does not exceed the onset point of network congestion. This two-pronged strategy enables rapid and congestion-aware bandwidth estimation, which is essential for computing the adaptive factor α in the rate control model. The system adopts a heuristic formulation in which the target encoding bitrate R is calculated as $R = R_{\text{initial}} \times \alpha \times f(\text{PLR}, \text{RTT})$, where α is dynamically adjusted based on observed bandwidth conditions. This design allows the system to promptly reduce the encoding rate under high PLR or RTT and to increase it conservatively as network conditions improve.

Data compression is achieved through a coding algorithm specifically optimized for speech characteristics, significantly reducing transmission data volume while preserving speech intelligibility and acoustic clarity. Transmission path optimization uses a measurement-based dynamic path selection (MDPS) algorithm, continuously monitoring latency, jitter, and packet loss across available paths to edge nodes. A centralized software-defined networking (SDN) controller steers traffic based on quality-of-service measurements. Buffer management dynamically adjusts buffer size to balance latency and smoothness, while predictive transmission pre-delivers translation resources based on user behavior. Edge computing deployment utilizes a three-tier architecture—central cloud, regional data centers, and over 50 geographically distributed edge nodes near major tourist hubs and textile clusters—ensuring most user requests are routed to a nearby node, reducing round-trip time and improving real-time responsiveness.

Parallel transmission technology employs multiple simultaneous paths to enhance reliability and speed. A congestion-aware intelligent load balancing algorithm allocates data segments across multiple paths (e.g., WiFi and 4G/5G), maximizing throughput while minimizing network impact. The comprehensive network communication solution incorporates transmission optimization, coordination mechanisms, and adaptive switching to address complex and variable network environments in tourism scenarios [10,11].

Performance metrics in Figure 1 derive from benchmark tests comparing the proposed system against standard commercial real-time streaming translation solutions utilizing TCP, under simulated international tourism conditions (average network baseline: 150 ms RTT, 3% packet loss rate).

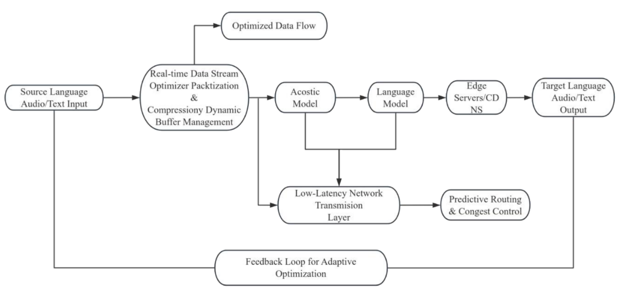

FIGURE 1. Low-Latency Real-Time Translation Network Transmission Optimization Architecture

B. HYBRID COMMUNICATION MECHANISM: OFFLINE CACHING AND CLOUD COLLABORATION

Given unreliable network coverage in travel scenarios, the system employs a hybrid communication model combining offline caching and cloud collaboration to maintain essential translation services during limited connectivity. Offline caching stores translation models, frequently used vocabulary, common sentence patterns, and conversation templates hierarchically on user devices. An intelligent preloading algorithm analyzes user itineraries and usage history to pre-download relevant resources. Cloud-based collaboration synchronizes and updates local caches when connectivity is restored, ensuring resource timeliness and accuracy.

The hybrid decision engine dynamically selects between local and cloud-based processing according to network conditions, translation complexity, and available computational resources. The switching strategy is governed by a dynamic threshold derived from the Network Quality Index (NQI), a composite metric integrating latency and packet loss rate. When the NQI exceeds 80 (e.g., RTT $<$ 100 ms, PLR $<$ 1%), the system operates in Online Mode. When the NQI falls below 30 (e.g., RTT $>$ 800 ms, PLR $>$ 10%), it switches to Offline Mode.

A Blend Mode is activated under marginal connectivity conditions, defined by an NQI between 30 and 80. In this mode, the engine simultaneously leverages locally cached resources for rapid translation of common phrases and the cloud-based Transformer models for complex, specialized, or low-frequency content, thereby maximizing both response speed and translation accuracy under intermittent network conditions. Incremental updates are implemented through a Delta Synchronization protocol, which computes and transmits only the difference blocks between the client's local cache and the latest cloud version, substantially reducing synchronization overhead. A version control mechanism maintains consistency between offline and online resources, preventing translation errors arising from version mismatches. For conflict resolution— particularly during concurrent updates to the specialized terminology database—the system primarily adopts a Last-Writer-Wins policy, supplemented by a Semantic Merge strategy for high-priority structured ontology data to preserve data integrity.

To ensure service continuity during network disruptions, a fault-tolerant mechanism enables seamless fallback to offline operation and automatically resumes unfinished translation tasks upon network restoration. During connectivity interruption, all user interactions, personalized configuration changes, and newly identified local terms are reliably logged on the client device. Once network connectivity is restored, a bidirectional synchronization process is initiated: the client first retrieves the latest official resources from the cloud and subsequently uploads accumulated local data—including usage logs and user feedback—to the cloud service center for collaborative learning and global model refinement. The overall hybrid communication framework of offline caching and cloud collaboration, illustrated in Figure 2, ensures the continuity and reliability of translation services through intelligent local storage and cloud-based synchronization strategies [12,13].

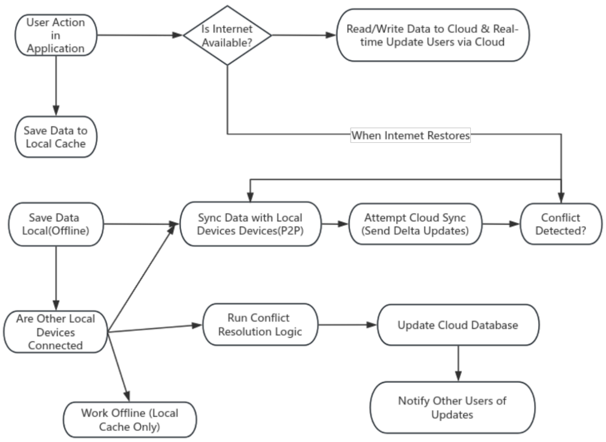

FIGURE 2. Architecture Diagram of Offline Caching and Cloud-Based Collaborative Hybrid Communication Mechanism

C. ADAPTIVE HANDOVER MECHANISMS IN MULTI-NETWORK ENVIRONMENTS

Tourism scenarios utilize diverse network environments, including WiFi, 4G/5G, and satellite networks. To ensure seamless connectivity across heterogeneous networks, the system incorporates an adaptive handover mechanism that begins with the construction of a multi-dimensional network quality assessment framework. This framework comprehensively evaluates key metrics, including signal strength, latency, packet loss rate, and available bandwidth. Network quality is quantified using a composite NQI, in which Signal Strength, Latency, and Packet Loss Rate are weighted at 30%, 40%, and 30%, respectively, thereby emphasizing latency as the dominant factor in handover decisions. A real-time monitoring module continuously collects status information from all available networks to generate an up-to-date network quality profile. Based on this profile, a machine learning–driven handover decision algorithm estimates the optimal handover timing and selects the most suitable target network. The intelligent switching engine utilizes a deep Q-network (DQN) for handover prediction, considering current NQI, user velocity, and predicted congestion to minimize service interruption.

Session persistence and state synchronization ensure uninterrupted translation during handovers. Multi-link aggregation enhances bandwidth and reliability, and intelligent load balancing allocates traffic based on network performance. A network prediction model powered by a long short-term memory (LSTM) neural network forecasts imminent network degradation, enabling proactive resource preparation. A fault recovery mechanism rapidly switches to backup networks during failures and reverts to the primary network upon recovery. The protocol adaptation layer manages compatibility across network types, ensuring smooth access for high-level applications. This adaptive switching mechanism significantly improves system stability and availability in complex network environments, delivering continuous translation services to international tourists [14]. The architecture diagram of the adaptive switching mechanism in a multi-network environment is shown in Figure 3:

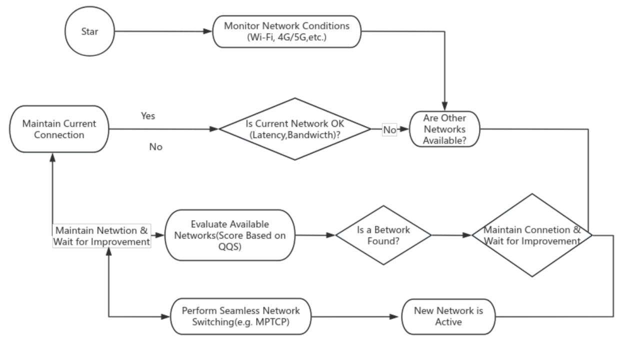

FIGURE 3. Architecture Diagram of Adaptive Switching Mechanism in Multi-Network Environments

IV. SYSTEM APPLICATION AND SERVICE QUALITY IMPROVEMENT STRATEGIES

A. USER INTERFACE DESIGN AND INTERACTIVE EXPERIENCE OPTIMIZATION

The user interface (UI) functions as the primary medium for visitor interaction with the translation system, with design quality directly affecting usability and satisfaction. The interface adopts a simple, intuitive layout with a flat design and clear visual hierarchy, facilitating efficient user experiences. Multilingual support enables automatic language switching based on device settings, offering a localized experience. Frequently used functions are prominently positioned, and operational processes are streamlined. Visual feedback, such as real-time sound wave graphics and voice recognition status, enhances user confidence.

Translation results are presented in multiple formats, including text-to-speech playback and pinyin annotation, catering to diverse needs. Gestures and shortcuts expedite common tasks. Personalization options permit adjustments to font size, color schemes, and function placement. Accessibility features support users with visual and hearing impairments through screen readers and vibration feedback, while responsive layouts ensure optimal display across device sizes. The user onboarding system employs tutorials and prompts to guide new users. Interface performance optimization minimizes page loading times, reduces operational delays, and improves interaction fluency. Collectively, these design and optimization measures contribute to a user interface that is both efficient and user-friendly. To empirically assess the effectiveness of the interface optimization, this study conducted a comparative analysis of user performance across multiple operational tasks before and after the optimization. The corresponding evaluation results are shown in Table 1 [15]. A standardized 5-point Likert scale questionnaire was administered to participants post-task, focusing on translation fluency, real-time response speed, and overall usability. Data was collected over four weeks from 210 international tourists and 45 textile industry professionals.

TABLE 1. Comparative analysis of operational effects before and after user interface optimization

Test Item	Average Time Before Optimization (s)	Average Time After Optimization (s)	Improvement (%)	User Satisfaction Rating	Number of Incorrect Operations
Starting recognition function for the first time	28.5	12.3	56.8	4.2/5.0	1.8
Language switching operation	15.2	6.7	55.9	4.5/5.0	0.9
Translation result adjustment	22.1	9.4	57.5	4.3/5.0	1.2
Personalized settings configuration	45.6	18.9	58.6	4.1/5.0	2.3
Offline mode switch	31.8	14.2	55.3	4.4/5.0	1.5
Urgent translation assistance	19.7	8.1	58.9	4.6/5.0	0.7

Analysis of Table 1 indicates that UI optimization significantly enhanced the efficiency and usability of the translation system. Average completion times for all six operational tasks decreased by over 55%, with "Urgent translation assistance" achieving the highest efficiency gain at 58.9%. The number of incorrect operations was nearly halved, confirming the intuitive design. User satisfaction ratings ranged from 4.1/5.0 to 4.6/5.0, validating the effectiveness of the streamlined interface and visual feedback mechanisms.

B. SCENARIO-BASED DEPLOYMENT AND PERSONALIZED SERVICE STRATEGIES IN SCENIC AREAS

Scenario-based deployment in scenic areas increases the practicality of the translation system by integrating it into specific tourism environments, enabling more accurate and personalized services. The system customizes resource allocation and functional module deployment based on the unique characteristics of each scenic area. Historical and cultural sites emphasize translation capabilities for cultural relics and historical references, ensuring accurate cultural transmission. Natural scenic areas prioritize translation of geographical and ecological vocabulary, while theme parks enhance real-time translation for entertainment programs and safety reminders.

Location-aware services utilize GPS and geo-fencing technology to automatically switch to specialized modes. Personalized recommendation engines analyze visitor interests, preferences, and browsing history to proactively deliver relevant translation content and cultural background information. Multi-terminal collaboration supports a range of devices, including smartphones, tablets, and smart glasses, providing seamless experiences. Integration with electronic maps and audio guides offers one-stop service within scenic areas. Group translation enables instant multilingual communication between tour guides and tourists, while an emergency response module facilitates rapid translation of medical and safety information. Service quality assurance is achieved by linking with scenic area management systems to ensure official and accurate translation content.

Data from a six-month field survey across 15 major scenic areas in three Chinese provinces (Jiangsu, Sichuan, and Shaanxi) demonstrate the effectiveness of scenario-based deployment. Behavioral observation and post-use structured interviews were conducted, and system logs were analyzed. A total of 1,850 interactions from 450 distinct international tourists were evaluated using descriptive statistics. Table 2 summarizes the results.

TABLE 2. Survey data on the effectiveness of scenario-based translation services in different types of scenic spots

Scenic Spot Type	Average Daily Usage (sessions)	Translation Accuracy (%)	Tourists' Willingness to Recommend (%)	Average Length of Stay Increase (%)	Service Complaint Rate (‰)	Cultural Understanding Satisfaction
Historical and cultural spots	1,245	94.2	87.3	32.1	2.1	4.7/5.0
Natural scenic area	892	91.8	82.6	28.7	3.2	4.4/5.0
Theme park	1,567	89.5	85.1	25.4	4.1	4.2/5.0
Ancient town/water village	734	93.6	89.2	35.8	1.8	4.8/5.0
Modern urban landscape	1,123	88.7	79.4	22.3	5.3	4.0/5.0
Religious and cultural sites	456	95.1	91.7	41.2	1.5	4.9/5.0

The high willingness to recommend (up to 91.7%) and low complaint rates across all scenarios confirm that context-specific translation resources enhance tourist experience and cultural understanding. The theme park scenario exhibits the highest usage but the lowest increase in length of stay, attributed to the structured nature and operational hours of theme parks, which limit the potential for extended visits despite high translation demand.

C. SYSTEM PERFORMANCE EVALUATION AND CONTINUOUS OPTIMIZATION MECHANISM

A comprehensive performance evaluation and continuous improvement mechanism is essential for ensuring long-term stability and ongoing enhancement of the translation system. The evaluation employs multidimensional indicators, including technical metrics (translation accuracy, response time, system stability, resource utilization) and operational metrics (user satisfaction, usage frequency, problem-solving efficiency). To validate the technical superiority of the multimodal translation engine, comparative evaluations were conducted against a leading commercial translation tool under real-world tourism scenarios. Tests utilized standard consumer smartphones (Samsung Galaxy S21, iPhone 13 Pro) in laboratory locations (Beijing and Shanghai) connected via dedicated links, with network conditions emulated to simulate international roaming. The evaluation sample comprised 3,500 unique English-to-Chinese parallel sentences, drawn from the WMT'17 dataset and a proprietary Tourism Terminology Dataset. Five-fold cross-validation ensured robust model assessment. Environmental noise was simulated using 10 dB SNR audio from the MUSAN dataset, and image-based text scenarios included 800 photos of tourism signs.

1) Evaluation Criteria

Both the BLEU Score and the TER metrics were computed using the open-source SacreBLEU library (version 2.0.0). Tokenization was standardized using the zh-tok scheme for Chinese (target language) and the mteval-v13 standard for English (source language), based on a multi-reference evaluation corpus.

The BLEU Score (Bilingual Evaluation Understudy) ranges from 0 to 1, with higher values indicating greater translation fidelity. The TER Score (Translation Error Rate) measures the minimum number of edits required to transform the system output into a reference translation, normalized by the reference length; lower TER values therefore indicate higher translation quality. Human evaluation was conducted on a five-point scale, where 1 denotes completely incomprehensible output, 3 indicates adequate meaning with poor fluency, and 5 represents perfect semantic accuracy and fluency.

As summarized in Table 3, the experimental results demonstrate substantial improvements across key translation quality metrics, particularly in scenarios involving environmental noise and image-based inputs. To support continuous performance assessment, the automated testing platform periodically conducts benchmarking and stress testing to proactively identify performance bottlenecks. User feedback is collected through in-app reviews, structured questionnaires, and usage behavior analysis, enabling systematic identification of user needs and pain points.

Furthermore, extensive usage log analysis is employed to detect recurring error patterns and guide targeted system refinements. An A/B testing framework is used to validate the effectiveness of newly introduced features and optimization strategies. The knowledge base is continuously updated with emerging travel-related terminology and usage patterns to maintain content relevance. Model performance is iteratively enhanced through continual learning from newly acquired translation samples.

Finally, a real-time fault diagnosis mechanism monitors system components to enable rapid issue detection and resolution, while version management and rollback mechanisms ensure the secure and controlled system updates. Regular expert evaluations and third-party audits provide independent assessments and actionable recommendations. Collectively, this comprehensive evaluation and optimization framework ensures the sustained improvement of translation quality, system reliability, and overall service performance.

TABLE 3. Comparative Evaluation of Translation Quality in Real-World Scenarios

Evaluation Metric	Test Scenario	Proposed System Score	Baseline System Score
BLEU Score	Voice with Environmental Noise (ASR→MT)	0.85	0.78
BLEU Score	Image-Based Text (OCR→MT)	0.88	0.82
TER Score	Voice with Environmental Noise (ASR→MT)	0.15	0.22
TER Score	Image-Based Text (OCR→MT)	0.12	0.18
Human Evaluation (1–5)	Voice with Environmental Noise (ASR→MT)	4.2/5.0	3.8/5.0
Human Evaluation (1–5)	Image-Based Text (OCR→MT)	4.5/5.0	4.0/5.0

Table 3 presents a comparative analysis highlighting the superior performance of the proposed multimodal system. In noisy voice scenarios, the system achieved a BLEU score of 0.85 versus 0.78 for the baseline, and a TER score of 0.15 versus 0.22, indicating fewer post-editing errors. The greatest gains were observed in image-based text translation, with a BLEU score of 0.88 and a TER score of 0.12, confirming the efficacy of the integrated CNN/OCR pipeline. Human evaluation scores consistently exceeded the baseline, demonstrating enhanced translation quality and fluency as perceived by assessors.

V. CONCLUSION

The intelligent English translation system, designed for international tourists and the global textile supply chain, integrates advanced technologies including deep learning, network communication optimization, and user experience design. The platform delivers high-precision language recognition, multimodal translation, and comprehensive cultural context processing. From a network perspective, it addresses low-latency transmission for real-time interpretation, offline and online collaboration for continuous access, and adaptive multi-network switching. In application, the system provides a superior user experience and personalized scenario-based services for both tourists and industry professionals. The rigorous evaluation and continuous improvement mechanisms ensure sustained enhancement of service quality and user satisfaction.

AUTHOR CONTRIBUTIONS

Liyang Tong designed, collected and analyzed the data, and drafted the manuscript. Liyang Tong conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Liyang Tong participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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ANIMAL RESEARCH SUBJECTS

This study was approved by the Ethics Committee of Tieling Normal College, and was performed in accordance with the principles of the Declaration of Helsinki. All eligible participants signed an informed consent form. Descriptive statistics measured central tendency and dispersion.

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Not applicable.

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