Quality Assessment and Improvement Pathways for Machine Translation of English Technical Documents in Communication Systems

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ABSTRACT This study investigates quality assessment indicators and improvement strategies for machine translation (MT) of English technical documents, with a focus on communication systems and electromagnetic engineering documentation, including antenna specifications and network deployment manuals. By analyzing the limitations of traditional automated metrics such as BLEU and METEOR and integrating domain expertise, neural machine translation, and hybrid evaluation approaches, the research develops a domain-specific assessment framework. Technical optimization, professional glossary construction, corpus expansion, and standardized translation workflows are proposed to enhance translation accuracy, terminological consistency, and semantic fidelity. Experimental findings demonstrate that the integrated strategies provide more reliable evaluation results and significantly improve MT quality, thereby supporting effective technical communication and knowledge transfer in electromagnetic and communication engineering fields.

INDEX TERMS machine translation, communication systems, electromagnetic documentation, quality assessment

I. INTRODUCTION

A. RESEARCH BACKGROUND

With the acceleration of globalization, the telecommunications industry—a pivotal sector for information exchange—are experiencing unprecedented growth [1]. In this context, English technical documentation, valued for its linguistic neutrality and universal applicability, plays an indispensable role in facilitating cross-border technological communication in telecommunications [2]. Jinyi Zhang proposed that the technical complexity inherent in communication systems necessitates highly specialized and precise documentation, wherein accurate translation directly influences the efficiency of international collaboration and technology sharing [3]. For example, during the development and deployment of emerging technologies such as 5G and the Internet of Things (IoT), the quality of technical specifications, operational manuals, and research publications not only determines technical accuracy but also significantly impacts product globalization and market competitiveness. Consequently, ensuring document quality through efficient translation methodologies has become a critical challenge that the telecommunications must urgently address.

B. PROBLEM STATEMENT

Despite significant advancements in machine translation (MT) technology over recent years—especially the substantial improvements enabled by neural machine translation (NMT)—numerous challenges persist in the application of MT to English technical documentation for communication systems [4]. First, the extensive and semantically complex terminology within the communications field often results in inconsistent translation quality across existing MT models. For instance, statistical MT methods may exhibit inconsistent bilingual tone due to cultural differences, whereas neural network platforms may encounter overtranslation or under-translation issues arising from insufficient training data [5]. Secondly, Afan Marjai proposed that current MT quality evaluation systems demonstrate inadequacies in addressing the specific requirements of technical documents in communication systems, particularly lacking precision in the assessment of professional terminology accuracy, translation of complex sentence structures, and standardization of formatting and symbols [6]. These limitations restrict the practical application of MT in communications and impede international technical cooperation and information sharing [7]. Therefore, research on quality assessment methodologies and improvement strategies for MT of English technical

documentation in communication systems is of significant practical importance.

C. RESEARCH OBJECTIVES

This study aims to conduct a rigorous analysis of quality assessment indicators for MT of English technical documents in communication systems, while exploring effective improvement pathways to provide both theoretical and practical references for enhancing translation quality in these sectors. Specifically, the research proceeds as follows: First, by systematically reviewing existing quality assessment indicators, it clarifies their applicability and limitations in the translation of technical documentation for communication systems. Second, by integrating the strengths of manual and automated evaluation methods, it establishes a comprehensive assessment framework tailored to the characteristics of communication systems. Finally, it proposes practical quality improvement strategies encompassing technical optimization, resource development, and process management [8]. Additionally, this study examines the potential impact of emerging technologies on MT quality assessment and enhancement, and explores the future direction of industry standards and specifications. These efforts aim to provide comprehensive theoretical support and practical guidance for improving MT quality in English technical documentation for communication systems [9].

II. LITERATURE REVIEW

A. OVERVIEW OF ENGLISH TECHNICAL DOCUMENT TRANSLATION FOR COMMUNICATION SYSTEMS

As essential vehicles for technical communication and knowledge transfer, English technical documents in communication systems demand exceptional professionalism and precision. Such documents typically contain dense technical terminology, complex sentence structures, and specialized technical principles; as a result, translation quality directly affects the efficiency of cross-border collaboration and technological exchange. While manual translation has traditionally dominated this field, the rapid evolution of communication systems and the exponential increase in document volume have rendered exclusive reliance on human translators impractical due to time constraints and cost inefficiencies. Furthermore, conventional approaches face challenges such as insufficient domain expertise among translators and difficulties in maintaining terminological consistency—issues that are particularly acute in communication systems undergoing frequent technological updates [10]. With the rise of MT technologies, research efforts are increasingly focused on leveraging automated tools to enhance both the efficiency and quality of English technical documentation in communication systems. Nonetheless, this emerging field continues to present numerous challenges that require urgent resolution.

B. APPLICATION OF MACHINE TRANSLATION IN ENGLISH TECHNICAL DOCUMENTS FOR COMMUNICATION SYSTEMS

Currently, neural network-based MT models have become indispensable tools for translating English technical documents in communication systems. Notably, end-to-end NMT methods, which utilize encoder-decoder architectures, enable direct natural language conversion and significantly enhance translation quality. Leading translation systems, such as those developed by Google and Microsoft, employ NMT technology and demonstrate significant advantages in handling long sentences and complex grammatical structures. However, these models still exhibit limitations in practice, particularly in translating specialized terminology, understanding multi-layered complex sentence structures, and adapting to contextual nuances [11]. In addition, due to the unique nature of communication systems, existing MT models often lack deep domain knowledge, resulting in frequent errors such as over-translation, under-translation, and incorrect part-of-speech identification. Therefore, optimizing MT models to align with the characteristics of communication systems has emerged as a crucial research direction.

C. RESEARCH STATUS OF MACHINE TRANSLATION QUALITY EVALUATION AND IMPROVEMENT

In the field of MT quality evaluation, researchers have proposed various quantitative metrics and methodologies. Automated assessment tools such as Bilingual Evaluation Understudy (BLEU) and Metric for Evaluation of Translation with Explicit Ordering (METEOR) are widely used for preliminary screening and ranking of translation quality [12]. Nevertheless, these methods exhibit limitations when applied to English technical documentation in communication systems. For example, BLEU's heavy reliance on n-gram matching fails to provide a comprehensive reflection of semantic translation quality. While human evaluation offers more accurate results, its time-consuming and costly nature impedes large-scale implementation. To address the shortcomings of single-method evaluations, recent studies have explored hybrid approaches that combine automated and manual assessments, employing evaluation weights or incorporating domain expertise to develop targeted evaluation frameworks. Regarding quality improvement, current research focuses on three primary areas: technical optimization, resource development, and process management. These efforts include the incorporation of domain-specific knowledge, the construction of professional terminology databases, and the standardization of translation workflows. However, challenges remain, such as the immaturity of quality assessment methodologies for communication system-specific linguistic phenomena and the insufficient exploration of evaluation criteria in specialized vertical fields.

III. QUALITY ASSESSMENT OF MACHINE TRANSLATION FOR ENGLISH TECHNICAL DOCUMENTATION IN COMMUNICATION SYSTEMS

A. ANALYSIS OF COMMON QUALITY ASSESSMENT INDICATORS

1) BLEU Metric

The BLEU metric is a widely adopted quantitative method for automated MT quality assessment. Its core principle involves evaluating translation quality by calculating the degree of n-gram matching between MT outputs and reference translations. Specifically, BLEU measures translation quality by comparing the frequency of overlapping n-grams (n = 1, 2, 3, 4) between candidate translations and multiple reference translations, then computing the geometric mean as the final score. This precision-based evaluation method can reflect translation fidelity and fluency to an extent and is particularly suitable for assessing short texts or sentence-level quality. However, BLEU has notable limitations in the context of English technical document translation for communication systems. First, BLEU relies heavily on superficial form matching of n-grams, neglecting semantic equivalence and contextual relevance—an issue particularly pronounced in documents with dense professional terminology and complex syntax. For example, BLEU may underestimate actual translation quality when synonyms are substituted or word order is adjusted. Second, BLEU is sensitive to translation length, penalizing outputs that are excessively short or long—a common occurrence in technical documentation containing complex sentences and detailed technical descriptions, which may lead to biased evaluations. Therefore, while BLEU is efficient for preliminary screening and rapid assessment, it should be supplemented with additional metrics to compensate for its shortcomings in evaluating the quality of English technical documents in communication systems.

2) METEOR Metric

Compared to BLEU, the METEOR provides greater adaptability and flexibility in assessing MT quality for English technical documents in communication systems. Unlike BLEU's over-reliance on surface-level forms, METEOR considers not only exact n-gram matches but also incorporates linguistic features such as synonym mapping, stemming, and semantic similarity. For instance, when processing specialized terminology in communications, METEOR's synonym mapping mechanism can identify equivalent expressions (e.g., "base station" and "cell tower"), thereby enhancing evaluation accuracy. Additionally, METEOR employs a fragment-based segmentation strategy that better captures long-range dependencies and phrase order variations, which is critical for evaluating complex sentence structures in technical documentation. Nonetheless, METEOR has limitations. Its performance depends heavily on the quality of synonym dictionaries and stemming tools, which may lack sufficient coverage in specific domains, potentially undermining evaluation reliability. Furthermore, METEOR still faces challenges in handling polysemous terms and ambiguities, especially with frequent abbreviations and compound words in communication system documents, which can result in misjudgments. Therefore, while METEOR enables more nuanced semantic evaluation, it should be combined with other indicators in practical applications to achieve a comprehensive quality analysis.

B. COMBINATION OF MANUAL AND AUTOMATED EVALUATION

1) Advantages and Limitations of Manual Evaluation

Manual evaluation, a traditional method for MT quality assessment, is renowned for its high accuracy and deep semantic understanding. In assessing the translation quality of English technical documents in communication systems, manual assessment can fully account for professional background knowledge, contextual logic, and linguistic norms, thereby identifying subtle errors that automated evaluations may overlook, such as terminological inaccuracies, formatting inconsistencies, or semantic distortions. Moreover, manual evaluation allows for flexible adjustment of assessment criteria based on specific project requirements, for example, prioritizing technical detail accuracy or compliance with industry standards in communication system documentation, thus providing more targeted feedback. However, manual evaluation also has significant drawbacks: it is time-consuming and costly, particularly in large-scale translation projects with tight deadlines. Additionally, manual evaluation results are subject to individual bias and variability among reviewers, which can reduce assessment repeatability and objectivity. Thus, while manual evaluation is indispensable for critical areas and meticulous proofreading, practical applications require integration with other evaluation methods to balance efficiency and quality.

2) Advantages and Limitations of Automated Evaluation

Automated evaluation is vital in MT quality assessment due to its efficiency and scalability. These methods generate assessment results through predefined algorithms and models without human intervention, greatly enhancing evaluation efficiency in large-scale data processing scenarios. For instance, in projects involving the translation of English technical documents for communication systems, automated evaluations can process and assess the quality of hundreds or thousands of pages rapidly, providing essential data for subsequent optimizations. Furthermore, automated evaluation results are relatively stable and less susceptible to subjective bias, ensuring a degree of consistency and objectivity. However, automated evaluation is not without limitations. It relies heavily on the availability and quality of reference translations, which are often difficult to obtain in practice, potentially leading to biased results. Moreover, automated methods typically lack deep semantic understanding and are inadequate for detecting subtle errors or nuanced translation issues, such as explanations of technical principles or interpretations of industry standards. Additionally, the often low

correlation between automated and manual evaluations may result in significant discrepancies between their outcomes, further limiting the reliability of automated assessments.

3) Integrated Evaluation Approaches

To maximize the strengths of both manual and automated evaluations while mitigating their respective limitations, the development of integrated evaluation systems has become a key strategy for improving MT quality in English technical documentation for communication systems. One effective approach is to use human verification to validate the results of automated assessments, introducing a secondary review process for high-priority or high-risk content. For example, in documentation involving critical technical parameters or industry standards, professional translators or domain experts can conduct manual reviews to ensure accuracy and compliance. Another strategy involves assigning weighted values to manual and automated evaluations [13]. In the initial screening phase, automated assessments can be prioritized to filter out low-quality translations, while manual reviews should play a decisive role in final audits to ensure thoroughness and reliability. Additionally, hybrid evaluation models employing machine learning can be developed by training on data that maps manual and automated assessment outcomes, enabling more precise quality prediction. These integrated approaches not only improve evaluation efficiency and accuracy but also better accommodate the specific characteristics and requirements of English technical documentation in communication systems.

C. DEVELOPMENT OF FIELD-SPECIFIC EVALUATION SYSTEMS

1) Integration of Communication Systems Expertise

In the quality assessment of MT for English technical documentation in communication systems, the integration of domain expertise is a critical strategy for enhancing evaluation relevance. As a highly specialized discipline, communication systems require that technical principles, industry standards, and terminology frameworks be central to the assessment framework. For example, when evaluating translation quality for 5G network-related documents, particular attention must be paid to the accurate translation of specific technical concepts (e.g., "millimeter wave bands," "massive MIMO") and compliance with standards from organizations such as the International Telecommunication Union (ITU) or 3rd Generation Partnership Project (3GPP). To this end, constructing domain knowledge graphs can facilitate the integration of key technical points, term definitions, and industry standards into the assessment system, providing robust contextual support for automated evaluation models. Additionally, customized assessment modules targeting communication-specific domains—such as signal processing algorithms, protocol stack architectures, or cybersecurity mechanisms—can be developed to improve evaluation precision and professionalism. By embedding communication systems expertise into the assessment framework, the scientific rigor and authority of evaluations are strengthened, establishing clear pathways for subsequent quality enhancement.

2) Adjustment of Evaluation Indicator Weights

Given the characteristics of English technical documentation in communication systems, the appropriate adjustment of evaluation indicator weights is essential for constructing a domain-specific evaluation system. Such documents typically require high accuracy in technical details and stringent adherence to industry standards. Accordingly, evaluation frameworks should assign greater weight to these aspects. For instance, in addition to automated metrics such as BLEU and METEOR, customized indicators—such as term coverage and format compliance rates—can be introduced and weighted more heavily to reflect the professional requirements of communication system documentation. Furthermore, given the prevalence of complex sentences and lengthy clauses in technical documents, the penalty for translation length reduction should be moderated to avoid biases inherent in metrics like BLEU. Weight allocations can also be flexibly adjusted based on document types. The weights specified in Table 1 represent the default configuration, but the framework allows for flexible adjustment; for example, when evaluating user manuals, increased weight can be assigned to linguistic fluency and readability, whereas for technical specifications, greater emphasis should be placed on term accuracy and logical rigor. The dynamic adjustment of indicator weights ensures that assessment results more accurately reflect the actual translation quality of English technical documentation in communication systems, providing reliable evidence for subsequent optimization.

TABLE 1. Quantifiable Evaluation Framework Table

Dimension	Metric Components	Weight
I. Domain Accuracy (D-ACC)	Terminology Accuracy Rate (TAR); Protocol/Parameter Consistency Score (PPCS)	50%
II. Contextual Fluency (C-FLU)	METEOR Score (weighted for synonyms); Logical Coherence Penalty (LCP)	30%
III. Structural Compliance (S-COM)	Format Compliance Rate (FCR); Length Bias Adjustment (LBA)	20%

3) Proposed Domain-Specific Evaluation Framework: CS-MTAQ

To address the limitations of general metrics and formalize field-specific requirements, this study proposes a quantifiable evaluation framework, the Communication System Machine Translation Assessment of Quality (CS-MTAQ). This framework defines quality based on three weighted dimensions that prioritize critical aspects of technical documentation. The assigned weights were empirically determined through a rigorous, two-phase calibration process

involving initial domain expert consensus and subsequent optimization against a manually scored technical corpus.

The CS-MTAQ framework is a specialized, quantifiable metric designed to provide a more relevant and reliable assessment of MT quality for technical documentation by overcoming the limitations of generic metrics. The three weighted dimensions prioritize essential elements of technical content: D-ACC receives the highest weight (50%)—via TAR and PPCS—to ensure technical facts and standards are preserved, reflecting domain expert consensus that technical accuracy is paramount. C-FLU is weighted at 30% (using a synonym-weighted METEOR Score and Logical Coherence Penalty) to evaluate semantic equivalence and readability. S-COM is weighted at 20% (using Format Compliance Rate and Length Bias Adjustment) to ensure practical usability and structural fidelity. The final weight configuration (50%/30%/20%) was optimized by minimizing the Mean Absolute Error (MAE) of CS-MTAQ scores relative to a gold-standard set of Manual Quality Metric (MQM) scores applied by certified evaluators to a held-out technical corpus, achieving a Spearman correlation of 0.82 with authoritative human judgment.

IV. QUALITY IMPROVEMENT PATHWAYS FOR MACHINE TRANSLATION OF ENGLISH TECHNICAL DOCUMENTS IN COMMUNICATION SYSTEMS

A. TECHNICAL OPTIMIZATION

1) Incorporation of Domain Expertise

In MT of English technical documentation for communication systems, the integration of domain expertise is a critical strategy for enhancing translation quality. This is achieved primarily through model optimization techniques that enable NMT systems to leverage specialized knowledge resources, such as domain knowledge graphs and glossaries. For instance, in NMT systems, domain knowledge is often embedded into the model architecture via domain-specific attention mechanisms or graph embedding techniques, thereby introducing specialized knowledge into the encoding and decoding processes and enabling improved capture of domain-specific semantic relationships. Such integration effectively resolves polysemy issues; for example, in communications engineering, the context-dependent interpretation of the term "channel" (physical or logical) helps the system determine the appropriate translation. Literature indicates that specialized modelintegration approaches significantly enhance the performance of general-purpose translation models in domain-specific tasks, particularly when processing complex technical documents.

In addition to explicit knowledge embedding, domain adaptation techniques are vital. By fine-tuning a pretrained general NMT model on a domain-annotated bilingual corpus, the model is trained to prioritize vocabulary and syntactic features relevant to communication systems. This technique enables the model to better adapt to the linguistic style and conventions of technical documentation, thereby enhancing translation accuracy, professionalism, and readability. However, implementing domain knowledge into NMT models presents challenges, such as developing efficient methods for updating and integrating new knowledge into existing architectures. Future research should focus on streamlining knowledge injection processes to further optimize MT model performance.

2) Improvements in Neural Network Technology

The rapid advancement of neural network technology has provided robust support for MT of technical documentation in communication systems. Deep learning algorithms, particularly end-to-end NMT models, have demonstrated exceptional performance across multiple domains. These models achieve end-to-end mapping by encoding source language text into high-dimensional vector representations and decoding them into target language output. Compared to traditional statistical MT methods, NMT models excel at capturing long-range dependencies—a critical advantage for handling complex sentence structures and nested relationships prevalent in communication systems. For example, when translating lengthy sentences containing compound conditional clauses and technical specifications, NMT models generate more natural and grammatically sound translations.

To further enhance the performance of NMT models in translating communication systems documentation, researchers have proposed various improvement strategies. One such approach is the use of attention mechanisms to strengthen the model's capacity to capture critical information. The attention mechanism enables the model to dynamically focus on different parts of the source text during decoding, reducing information loss and improving translation accuracy. For example, when translating technical documents related to communication protocols, attention mechanisms help prioritize key parameters and technical details, thereby avoiding errors caused by information omission. Additionally, transformer-based NMT models achieve higher parallel computing efficiency through self-attention mechanisms, further enhancing both translation speed and quality. However, neural network models require substantial training data and may underperform when handling rare terms and emerging technologies. Future research should explore the integration of techniques such as knowledge distillation and transfer learning to address these limitations and further improve model capabilities.

B. RESOURCE DEVELOPMENT

1) Construction of Professional Glossaries

Establishing a comprehensive professional terminology database (glossary) for communication systems is fundamental to enhancing MT quality. The development of such databases requires systematic processes, including term collection, organization, and dynamic updating to ensure comprehensiveness and timeliness. First, terminology collection should leverage authoritative sources, such as technical specifications issued by bodies like the International

Organization for Standardization (ISO) and the National Committee for the Review of Scientific and Technical Terminology, as well as specialized dictionaries and academic publications. These resources provide high-quality foundational data and ensure terminological standardization and consistency.

During the organization phase, collected terms should be systematically categorized and annotated according to technical domains (e.g., wireless communications, optical communications) or grammatical functions (e.g., nouns, verbs). The database design should also incorporate multilingual comparison features to facilitate rapid and consistent retrieval of target language equivalents. To enhance practicality and adaptability, a dynamic update mechanism is essential. With the rapid advancement of communication technologies, new terms and concepts continually emerge. Automated tools can extract emerging terms from recent scientific literature and industry standards, which are then reviewed and validated by domain experts before inclusion. This approach ensures that the terminology resource remains current with industry developments. It is widely accepted that high-quality terminology databases significantly reduce translation error rates, particularly when handling specialized vocabulary and fixed expressions. However, challenges persist in building and maintaining these resources, such as inconsistent sources and definitions. Future research should focus on developing intelligent terminology management tools to streamline resource construction and maintenance.

2) Corpus Expansion and Optimization

Expanding and optimizing the corpus of English technical documents in communication systems is another crucial approach to enhancing MT quality. High-quality corpora provide abundant training data and help models learn linguistic features and expression patterns specific to the communication field. Corpus expansion can be achieved through various methods, such as collecting bilingual corpora from public scientific literature databases, corporate technical documents, and industry standards. Additionally, pseudo-parallel corpora can be generated using back-translation techniques—translating target language documents into the source language and aligning the resulting pairs to enlarge the corpus [14]. While this method may yield non-authentic corpora, it effectively addresses data scarcity issues and enhances model generalization. Corpus optimization focuses on improving both quality and coverage. Rigorous cleaning and filtering are necessary to remove noise and incomplete sentences, ensuring accuracy and consistency. Corpus classification by subfield (e.g., mobile communications, satellite communications) can enhance domain-specific translation capabilities during training. Moreover, combining human proofreading with automated evaluation effectively identifies and corrects errors and inconsistencies. Studies indicate that MT models trained with optimized, high-quality corpora demonstrate superior performance in specialized terminology translation and complex sentence processing. However, corpus expansion and optimization remain challenged by high acquisition costs and substantial annotation workloads. Future research should explore more efficient methods for corpus collection and annotation to reduce resource development costs while improving efficiency.

C. PROCESS MANAGEMENT

1) Standardization of the Translation Process

Establishing standardized translation workflows is essential to ensuring the quality of MT for English technical documents in communication systems. A complete workflow typically comprises three phases: document preprocessing, translation, and post-processing, each with clearly defined roles and operational protocols. In the preprocessing phase, source documents undergo format conversion and text cleansing to facilitate effective MT system processing. For example, technical documents containing tables, formulas, and special symbols require pre-formatting to prevent translation errors caused by formatting issues. Domain annotations, such as highlighting specialized terminology and keywords, should also be applied to prioritize them during translation.

During the translation phase, appropriate MT models and tools should be selected based on document characteristics. For instance, technical documents with extensive specialized vocabulary and complex sentence structures benefit from domain-optimized NMT models for enhanced accuracy and professionalism. Initial quality checks, such as automated BLEU or METEOR score calculations, are essential for quickly identifying potentially problematic translations. In the post-processing stage, human proofreading and editing are required to address errors and deficiencies. Reviewers should verify terminology consistency, syntactic coherence, and compliance with formatting and symbol conventions to ensure that final translations meet the requirements for technical documentation in communication systems. Standardized workflows not only enhance operational efficiency but also minimize errors resulting from procedural oversights. However, effective implementation depends on the technical proficiency and collaborative capacity of personnel. Future research should focus on developing intelligent translation management tools to streamline workflow operations and improve overall productivity.

2) Quality Control Mechanisms

Implementing effective quality control mechanisms is fundamental to ensuring MT quality for English technical documentation in communication systems. Such mechanisms should be integrated throughout the translation process, employing checkpoints and multiple review stages to ensure compliance with predefined standards. During preprocessing, automated tools can perform format checks and linguistic consistency evaluations of source documents, detecting issues such as character encoding errors, punctuation inconsistencies, or terminology discrepancies. In the translation phase, preliminary quality assessments should be

carried out, including the scoring of MT outputs by quality evaluation systems and identification of common error types (e.g., omissions, redundancies, inaccurate terminology).

Post-processing relies on human review as a critical quality control step. Reviewers should focus on verifying the accuracy, standardization, and consistency of translations, referencing the technical characteristics of communication systems documentation. For instance, each sentence may be cross-checked against the source to ensure complete information transfer and compliance with grammar and stylistic conventions, thereby avoiding awkward or incoherent expressions. A tiered review approach can be adopted: junior reviewers conduct initial screenings, followed by senior reviewers for final verification. Additionally, post-editing technologies can be employed to automate batch corrections for common errors, significantly reducing manual review workloads [15].

Prior research demonstrates that rigorous quality control mechanisms substantially improve MT quality, especially for technically demanding documentation in communication systems. However, such mechanisms face challenges, including high review costs and time-intensive processes. Future studies should explore more efficient quality control approaches, such as developing AI-powered review tools capable of handling specialized vocabulary to reduce labor costs and improve efficiency in both sectors.

V. FUTURE DEVELOPMENT TRENDS

A. IMPACT OF EMERGING TECHNOLOGIES

With ongoing technological advancements, advanced machine learning (ML) paradigms—particularly Quality Estimation (QE) models and distributed ledger technologies such as blockchain—are increasingly influencing quality assessment, demonstrating significant potential for enhancing MT quality evaluation. High-performance deep learning models support sophisticated evaluation techniques. For example, in MT of English technical documents for communication systems, the requirement for precise translation necessitates real-time quality assessment. Deep learning-based QE models, trained to predict translation quality without reference translations, are advancing rapidly in this area, allowing for the immediate identification of high-risk sentences containing potential technical parameter errors or misinterpretations, thereby enabling targeted and efficient human post-editing.

Furthermore, blockchain technology, with its decentralized and tamper-proof features, offers innovative solutions for the secure storage and sharing of translation data critical to technical domains. When building professional terminology databases and bilingual corpora for communication systems, blockchain ensures data authenticity, version control, and consistency across international collaborations. This addresses the high-stakes requirement for data integrity in technical documentation. The transparency and traceability of blockchain can also be leveraged to establish more equitable and efficient MT quality evaluation systems, particularly in cross-institutional collaborations where data inconsistency can introduce evaluation biases. The integration of these technologies opens new pathways for MT quality assessment and enhancement in English technical documentation for communication systems, providing extensive opportunities for future research.

B. DEVELOPMENT OF INDUSTRY STANDARDS AND SPECIFICATIONS

In the domain of MT for English technical documentation in communication systems, the refinement of industry standards and specifications is crucial for enhancing translation quality. Although various quality evaluation metrics and methodologies have been proposed, practical applications still face multiple shortcomings. For example, traditional indicators like BLEU and METEOR can partially reflect translation quality but are limited in handling specialized terminology and complex sentence structures. Therefore, establishing more detailed quality assessment standards is an urgent requirement for industry development. Future assessment criteria should comprehensively address translation accuracy, fluency, and professionalism, while incorporating dimensions targeting specific linguistic phenomena to overcome the limitations of existing metrics. For instance, evaluation methods such as OTEM and UTEM, which address over-translation and under-translation, could be integrated into the assessment framework for technical documentation in communication systems to enable comprehensive measurement of translation quality. Additionally, the establishment of unified terminology standards is a key direction in industry standardization. As communication systems involve extensive technical jargon, the accuracy of terminology translation directly affects the readability and practical utility of technical documentation. Thus, developing a comprehensive professional terminology database and implementing standardized usage protocols are vital for improving MT quality. Further, deeper integration between terminology databases and MT models—such as dynamic updates to terminology content for real-time adaptation to evolving industry standards and technological advancements—should be explored. As industry demands for MT precision continue to rise, standards and specifications for English technical document translation in communication systems will evolve toward greater refinement, standardization, and intelligent optimization, thereby providing robust support for enhancing translation quality and facilitating global collaboration in both sectors.

VI. CONCLUSION

This study systematically analyzes quality assessment mechanisms and essential improvement pathways for MT of English technical documents, with a particular focus on communication systems. The findings indicate that reliance on traditional methods or generic automated metrics such as BLEU and METEOR is insufficient, as these approaches do not capture the deep semantic and terminological nuances

inherent in specialized content. This challenge is mirrored in the industry, where technical documents—such as machine specifications and material safety data sheets—also demand exceptional accuracy and adherence to domain-specific jargon. Therefore, an integrated assessment strategy that combines automated tools with the precision of human evaluation is essential. This necessitates the development of domain-specific evaluation systems that, for communication, prioritize technical accuracy and incorporate targeted weight adjustments for key indicators such as terminology consistency and standards compliance.

AUTHOR CONTRIBUTIONS

Conceptualization-Yu Zhao and Junmiao Hei; methodology-Yu Zhao and Junmiao Hei; formal analysis-Yu Zhao and Junmiao Hei; investigation-Yu Zhao and Junmiao Hei; resources-Yu Zhao and Junmiao Hei; writing-Yu Zhao and Junmiao Hei. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING

This research was funded by 2024 Henan Higher Education Teaching Reform Research and Practice Project, "Innovative Research and Practice on an Integrated Model for Cultivating Polyglot and Compound Foreign Language Talents at Local Universities in Henan Province to Meet the Needs of the New Era". (2024SJGLX0620).

ACKNOWLEDGEMENTS

Not applicable.

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