***Minireview Article***

Research on the Transforming Translation Project Management with Large Language Models

Abstract

This paper systematically explores the technical characteristics of large language models (LLMs) and their transformative role in translation practice and project management. Built on the Transformer architecture and trained on massive textual corpora, LLMs exhibit generative, interactive, and multifunctional capabilities, enabling breakthroughs in translation tasks. The study first defines LLMs as deep learning models based on extensive text training and Transformer architecture, capable of performing diverse tasks such as translation and text generation. It then analyzes the application value of LLMs in translation practice, including improvements in translation quality, support for multimodal translation, and the intelligent upgrading of computer-assisted translation (CAT) tools. Furthermore, the paper outlines the traditional workflow of translation project management—initiation, planning, execution, monitoring, and closure—and highlights the transformative impact of LLMs on key stages, particularly initiation, execution, and revision. Finally, it identifies future trends, such as the evolution of project management toward intelligence and collaboration, and the expansion of quality assessment criteria to include cultural adaptability and user experience. The study also addresses emerging challenges, including ethical risks, the need for translator skill transformation, and semantic biases in model outputs. To foster deep integration of human-machine collaboration, future efforts should focus on technological optimization, ethical standardization, and translator training.

Keywords: Large Language Model (LLM); Computer-Assisted Translation (CAT); Multimodal Translation; Translation Project Management; Human-Machine Collaboration; Workflow Reengineerin

**Introduction**

**1. Large Language Models: Concept**

1.1 Definition

A Large Language Model (LLM) refers to a deep learning model trained on massive volumes of text data. LLMs can comprehend and generate human language, performing tasks such as natural language understanding, translation, text classification, text generation, and question answering. In 2022, OpenAI formally launched the ChatGPT LLM for natural language text generation. Upon release, it rapidly garnered widespread attention from both academia and the general public. Incomplete statistics indicate that within two months of its launch, ChatGPT surpassed 100 million users. Subsequently, OpenAI released the GPT model, achieving significant breakthroughs in natural language generation. This model possesses not only text generation capabilities but also audio, image, and video generation abilities.[1]

The core technology of LLMs primarily relies on the Transformer architecture, which employs a self-attention mechanism to effectively capture long-range dependencies in text, substantially enhancing contextual understanding. Through pre-training and fine-tuning, LLMs achieve superior performance on specific tasks ’15,16]. During pre-training, models learn universal linguistic patterns from large-scale general corpora; fine-tuning adapts the model using domain-specific data to meet particular task requirements [17].

1.2 Characteristics of Large Language Models (LLMs)‌

Large Language Models are typically characterized by three salient attributes: ‌generativity‌, ‌interactivity‌, and ‌multifunctionality‌. Generativity‌ denotes an LLM’s capability to produce coherent textual outputs spanning conventional and multimodal formats. These outputs emulate human language in stylistic coherence and fluency. Beyond generating diverse textual content, LLMs can translate identical source-language text into multiple target languages. ‌Interactivity‌ refers to a user’s capacity to engage with LLMs using natural language [18-20]. Trained on linguistically diverse datasets encompassing varied topics, LLMs demonstrate proficiency in addressing heterogeneous user queries. Multifunctionality‌ enables LLMs to perform a spectrum of tasks, including but not limited to Text generation, Translation, Question answering‌, Dialogue, Sentiment analysis, Named entity recognition, and Text classification. ‌Text generation‌: Synthesizing grammatically and semantically coherent text; ‌Translation‌: Converting source-language input into target-language output; ‌Question answering‌: Providing responses to user inquiries; ‌Dialogue‌: Simulating human conversation by contextualizing inputs and generating natural language exchanges; ‌Sentiment analysis‌: Determining affective polarity (positive, negative, or neutral) in textual inputs; ‌Named entity recognition‌: Identifying structured entities (e.g., personal names, geographical locations, organizations) within text; ‌Text classification‌: Categorizing textual content into predefined classes based on specified criteria [1].

**2. Application of LLMs in Translation Practice**

LLMs hold immense potential in learning, daily life, and professional work. They are directly applicable to translation practice and can drive data-driven translation research. However, while presenting significant historical opportunities, they also pose major challenges for translation practice and research.

2.1 Translation Quality Enhancement

LLMs have catalyzed a qualitative leap in machine translation (MT) quality. The "Human+AI" hybrid language service model has experienced rapid growth. While "MT + Post-Editing" services saw initial rapid expansion followed by a growth plateau, Augmented Translation Memory, Automatic Content Enrichment, Machine Interpreting, and other Intelligent Multilingual Services are growing rapidly.[2]

Compared to traditional statistical MT and early neural MT, LLM-based MT demonstrates superior contextual semantic understanding, handling complex syntax and domain-specific terminology more effectively, resulting in significantly improved fluency and accuracy. For instance, specialized models in finance and healthcare (e.g., Du Xiaoman Xuanyuan, iFlyTek Spark Medical) achieve high-precision translations, reducing post-editing costs.

Augmented Translation integrates AI-driven technologies with human translators to enhance their efficiency and effectiveness (O’Brien, 2024: 393). Here, the translator remains central, leveraging technologies like translation memory, adaptive MT, automatic content enrichment, and terminology management to improve service efficiency, quality, and capability.

In terminology translation research, LLMs foster methodological innovation, offering new perspectives for theoretical and practical advancement. Leveraging powerful NLP capabilities, LLMs enhance term translation quality. Trained on large datasets like Wikipedia and Common Crawl (a public dataset collected via web crawling), LLMs learn multilingual structures and usages, generating multilingual term translations. This enriches and standardizes multilingual terminology, facilitating the horizontal expansion of research scope.[3]

2.2 Enabling Multimodal Translation

LLMs are ushering in a new era of multimodal translation. Utilizing multimodal pre-training and cross-lingual alignment technologies, their application extends to image, audio, and other multimodal content. Integrated with computer vision and speech recognition, LLMs accurately translate text within images and speech into target languages, expanding translation scenarios. For example, advanced Vision-Language Models (VLMs) like GPT-4V and Kimi K1 accurately interpret and translate image content, equipping AI translation with "vision" for descriptive translation of scenes.

In this new era, users act as conductors in human-AI interaction, employing optimized prompt engineering, Chain-of-Thought tuning, and contextual example injection to guide AI translation towards personalized outputs. This shift equips translation with delivering bespoke solutions.[4]

2.3 Intelligent Upgrade of Computer-Assisted Translation (CAT) Tools

CAT focuses on "how to apply computer software to maximize automation of the translation workflow, enhance human translator efficiency, ensure quality, and manage the process."[5] Undoubtedly, the rise of Generative AI and LLMs has spurred transformative change, redirecting technological innovation. Consequently, traditional language services are evolving towards intelligent language services, and the integration of AIGC tools with CAT software is emerging.[6]

AIGC tools integrated into CAT software's MT functionality can be used for pre-translation or sentence-by-sentence translation. Unlike traditional MT engines, project translation memories, or termbases, most AIGC outputs can be displayed alongside traditional MT matches, TM matches, and termbase matches in the translation interface for comparison and selection. Currently, AIGC tools in CAT software primarily support during-translation and post-translation stages, e.g., pre-translation source text analysis, intelligent text rewriting, bilingual alignment, and terminology extraction.

CAT tools integrated with LLMs provide real-time translation suggestions, automate repetitive content translation, and enable automatic terminology recognition and consistency, significantly boosting translator efficiency. Translators can thus focus more on optimizing and polishing translations rather than tedious repetitive tasks.[7]

**3. Translation Project Management Process**

As a traditional academic discipline, translation plays an increasingly vital role in today's globalized society. Concurrently, as a service, it integrates with other scientific fields, evolving into the practical, economically oriented discipline of Translation Project Management (TPM). TPM is a systematic process ensuring translation projects are completed within defined time, cost, and quality constraints. Treating translation services as projects and managing them scientifically enhances service quality and standardizes the industry.[8]

Modern project management encompasses nine core elements: Time Management, Communication Management, Risk Management, Procurement Management, Scope Management, Integration Management, Cost Management, Quality Management, and Human Resource Management. These interdependent elements work cohesively to ensure successful project execution.[9] The traditional TPM process comprises the following phases:

3.1 Initiation Phase

This phase determines project feasibility and authorizes commencement. Key activities include: data collection, requirement identification, goal setting, feasibility studies, stakeholder identification, risk assessment, strategy formulation, team assembly, and resource estimation. Though typically constituting only 5% of project duration, this phase is critically important.

3.2 Planning Phase

This phase develops actionable plans and schedules to achieve project objectives, typically consuming 20% of project time. Key activities include: appointing key personnel, developing project plans (covering quality standards, resources, budget, cash flow, schedule, WBS, etc.), and assessing project risks.

3.3 Execution Phase

This phase coordinates human and other resources to implement the plan. Overlapping significantly with the Monitoring and Controlling phase, it typically accounts for 60% of project duration. Key activities include: plan implementation, progress reporting, information dissemination, team motivation, and procurement.

3.4 Monitoring and Controlling Phase

This phase ensures project objectives are met through supervision, measurement, and corrective actions. Key activities involve effectively monitoring and adjusting project scope, schedule, cost, and quality, striving for optimal balance.

3.5 Closing Phase

This phase secures formal acceptance and conducts an orderly project conclusion, typically taking 15% of project time. Key activities include: product delivery, performance evaluation, documentation archiving, and lessons learned documentation.

**4. Translation Workflow in LLM-Enhanced Practice**

The rapid development of LLMs has revolutionized translation. China's LLM development emphasizes both indigenous innovation and industrial application. Leading companies like Baidu, Alibaba, and iFlyTek have launched globally competitive general models (e.g., ERNIE Bot, Tongyi Qianwen, SparkDesk). For vertical applications, Chinese enterprises leverage core LLM architectures to develop specialized models in government affairs (e.g., Yongwei Government LLM), healthcare (e.g., Qiyuan Critical Care LLM), industry (e.g., Antelope Industrial LLM), and education (e.g., SparkDesk Education LLM), demonstrating a unique development path.[10]

LLM integration has significantly altered the translation workflow, with key differences emerging in the following stages:

4.1 Initiation Phase

During pre-translation, LLMs support tasks like domain knowledge acquisition, file format conversion, pre-editing, corpus alignment, and term recognition/extraction. These utilize NLP, computer vision, pattern recognition, machine learning, and expert decision support systems within LLMs. With advancing Generative AI (GenAI), providers efficiently identify and extract domain terminology during pre-translation, aligning recognized terms into translation memory files.

4.2 Execution Phase

The traditional "Translate + Review" approach is inadequate for modern large-scale translation demands.[11] Historically, translators relied solely on personal expertise, consuming significant time and effort while yielding lower efficiency. In the LLM era, MT becomes integral. LLMs rapidly generate draft translations, shifting the translator's role from "translator" to "editor" and "polisher," primarily responsible for revising and refining MT output. Simultaneously, LLMs provide real-time suggestions and terminology prompts, aiding translators and ensuring terminological accuracy and professionalism.

4.3 Review Phase

Traditional review, dominated by manual effort, is time-consuming and prone to oversight. LLMs effectively assist reviewers. Upon receiving context-appropriate prompts, LLMs automatically perform comprehensive checks for grammatical errors, terminology consistency, and logical coherence, generating review reports. This allows human reviewers to focus on deeper quality aspects like accuracy, fluency, and cultural adaptation, enhancing overall review efficiency and quality.

**5. Conclusion**

In the era of Artificial Intelligence (AI), human society is undergoing profound transformations characterized by cross-boundary integration, human-machine collaboration, open collective intelligence, and ubiquitous connectivity. These developments are accelerating the transition toward intelligent systems across socioeconomic domains [12].

Regarding evolving trends, translation project management is becoming increasingly intelligent, with Large Language Models (LLMs) playing pivotal roles in automating and optimizing workflows—from requirement analysis to project summation. The rapid advancement of LLMs is reshaping translation project management from human-dominated processes toward human-machine partnerships. Collaborative efficiency continues to rise through LLM-enabled real-time cooperation and information sharing among project team members and between teams and clients, thereby enhancing responsiveness and operational execution. Simultaneously, translation quality assessment criteria are diversifying beyond traditional metrics like accuracy and fluency to prioritize cultural adaptation and user experience.

Nevertheless, complexities inherent in language—including flexible cross-cultural awareness and inherently human sensibilities required for communication—determine that machine translation cannot wholly supplant human translation [13]. LLMs also present challenges in translation project management. These encompass ethical concerns such as copyright disputes and data breaches, alongside shifting skill requirements for translators who must now possess LLM collaboration capabilities and cross-cultural communication competencies.

Furthermore, the generative AI era, exemplified by technologies like Generative Pre-trained Transformers (GPT), has reconceptualized traditional education paradigms. Critical thinking, creativity, communication skills, and collaborative aptitude are emerging as new educational imperatives. Traditional translation faces intensified competition, while technological demands impose higher standards on language service professionals, compounding pedagogical challenges in translation technology training [14].

In the future, the translation industry must proactively address the opportunities and challenges presented by large language models (LLMs), continuously exploring profound integration paradigms between LLMs and translation project management. This requires: firstly, enhancing research and development efforts on LLMs to improve translation quality and reliability; secondly, strengthening translator training programs to elevate their comprehensive competencies and technical proficiency; lastly, establishing comprehensive ethical guidelines and industry standards to ensure the healthy development of the translation sector. Through concerted efforts from all stakeholders, translation project management can be advanced toward higher quality and greater efficiency in its developmental trajectory.

Disclaimer (Artificial intelligence)

Author(s) hereby declare that NO generative AI technologies such as Large Language Models (ChatGPT, COPILOT, etc.) and text-to-image generators have been used during the writing or editing of this manuscript.

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