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A Comparative Study on Large Language Models' Accuracy in Cross-lingual Professional Terminology Processing: An Evaluation Across Multiple Domains

Hanlu Zhang[1], *Wenyan Liu*[1.2]

[1] *Master of Science in Computer Science, Stevens Institute of Technology, NJ, USA*
[1.2] *Electrical & Computer Engineering, Carnegie Mellon University, PA, USA*
Corresponding author E-mail: mkf26947@gmail.com

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Abstract

Cross-lingual professional terminology processing presents significant challenges for large language models (LLMs) due to the complexity and domain-specific nature of specialized vocabularies. This study conducts a comprehensive evaluation of five state-of-the-art LLMs across four professional domains: medical, legal, engineering, and financial terminology translation tasks. We developed a multi-domain terminology dataset containing 2,400 professional terms with human-annotated translations in six language pairs. Our experimental framework employs multiple evaluation metrics including BLEU scores, semantic similarity measures, and domain expert assessments. Results reveal substantial performance variations across domains and language pairs, with accuracy ranging from 67.3% to 89.6%. Medical terminology achieved the highest translation accuracy, while legal terminology presented the greatest challenges. Cross-lingual semantic consistency varied significantly between model architectures, with transformer-based models demonstrating superior performance in maintaining semantic integrity. Error pattern analysis identified three primary failure modes: contextual ambiguity resolution, morphological variation handling, and domain-specific concept mapping. These findings provide critical insights for improving LLM performance in specialized translation applications and highlight the need for domain-adaptive training approaches in multilingual terminology processing systems.

1. Introduction

1.1. Background and Motivation for Cross-lingual Professional Terminology Processing

The proliferation of large language models has revolutionized natural language processing capabilities across diverse linguistic tasks, particularly in multilingual applications where cross-lingual understanding becomes paramount[1]. Professional terminology processing represents a critical frontier in this domain, where specialized vocabularies demand precise semantic preservation across linguistic boundaries. Unlike general language translation tasks, professional terminology requires deep domain knowledge and contextual understanding that extends beyond surface-level linguistic patterns.

Contemporary LLMs have demonstrated remarkable capabilities in various educational and assessment contexts, with recent advances showing promising results in specialized domains such as automatic mathematical answer grading and meta-learning approaches[2]. The complexity of professional terminology processing stems from the inherent challenges of maintaining semantic accuracy while navigating cultural and linguistic variations that characterize different professional fields. These challenges become particularly pronounced when dealing with technical concepts that may lack direct linguistic equivalents across different languages.

The motivation for this research emerges from the growing demand for accurate cross-lingual professional communication in an increasingly globalized world. Financial institutions, medical organizations, legal practices, and engineering firms require reliable automated translation systems capable of handling

specialized terminology with high precision[3]. Current general-purpose translation systems often struggle with domain-specific terminology, leading to semantic distortions that can have significant professional consequences.

1.2. Research Challenges in Multi-domain Terminology Translation Accuracy

Multi-domain terminology translation presents several interconnected challenges that distinguish it from general language processing tasks. The primary challenge lies in the semantic preservation of specialized concepts that often carry domain-specific implications not captured by traditional translation approaches**Error! Reference source not found.**. Professional terminology frequently encompasses concepts that have evolved within specific cultural and professional contexts, making direct translation inadequate without comprehensive domain understanding.

The automated skill assessment paradigm has demonstrated the importance of fine-grained analysis in specialized domains, highlighting the need for precise evaluation methodologies that can capture subtle semantic variations[4]. Cross-domain performance evaluation becomes particularly complex when considering the varying levels of standardization across different professional fields. Medical terminology benefits from international standardization efforts, while legal terminology remains highly jurisdiction-specific, creating disparate challenges for automated processing systems.

Scalability concerns emerge when attempting to develop comprehensive evaluation frameworks that can accommodate the breadth of professional domains while maintaining assessment rigor[5]. The collaborative nature of human-AI interaction in specialized domains requires sophisticated evaluation approaches that can capture both semantic accuracy and practical utility. Advanced architectures for processing complex linguistic structures have shown promise in addressing some of these challenges, though significant gaps remain in cross-lingual applications**Error! Reference source not found.**.

Another significant challenge involves the dynamic nature of professional terminology, where new concepts and specialized vocabulary continuously emerge. Mathematical reasoning and grading systems have demonstrated the importance of adaptive evaluation methodologies that can accommodate evolving linguistic landscapes[6]. The integration of distributed processing architectures becomes essential when handling the computational complexity associated with large-scale multilingual terminology evaluation[7].

1.3. Research Objectives and Main Contributions

This research aims to establish a comprehensive evaluation framework for assessing LLM performance in cross-lingual professional terminology processing across multiple domains. The primary objective focuses on developing standardized evaluation methodologies that can reliably measure translation accuracy while accounting for domain-specific semantic requirements. Advanced optimization techniques have shown considerable promise in handling complex linguistic processing tasks, providing a foundation for our methodological approach[8].

Our investigation encompasses four distinct professional domains, selected to represent varying levels of terminological standardization and cross-linguistic complexity. The research design incorporates both quantitative and qualitative evaluation approaches, enabling comprehensive assessment of LLM capabilities and limitations. Systematic optimization approaches in complex systems provide valuable insights for developing robust evaluation protocols[9].

The study's contributions include the development of a multi-domain terminology dataset with expert annotations, establishment of standardized evaluation protocols for cross-lingual professional terminology assessment, and comprehensive analysis of error patterns across different LLM architectures. Collaborative frameworks that emphasize human-AI complementarity inform our approach to developing evaluation systems that capture both automated metrics and expert assessment criteria[10].

2. Related Work and Background

2.1. Large Language Models in Multilingual Natural Language Processing

The evolution of large language models in multilingual natural language processing has undergone significant transformation over the past decade, with architectural innovations driving substantial improvements in cross-lingual understanding capabilities. Bias mitigation approaches in automated systems have highlighted the importance of fair and equitable processing across different linguistic and cultural contexts[11]. Contemporary research has demonstrated that mathematical operation embeddings can effectively capture semantic relationships in specialized domains, providing foundational insights for professional terminology processing**Error! Reference source not found.**.

Recent developments in real-time anomaly detection systems have showcased the potential for LLMs to handle complex pattern recognition tasks across diverse domains[12]. These advances suggest that sophisticated

neural architectures can maintain semantic consistency while processing specialized vocabularies. Knowledge-enhanced dialogue generation systems have demonstrated the importance of incorporating domain-specific information into LLM training processes, particularly when dealing with heterogeneous knowledge sources**Error! Reference source not found.**.

Energy-efficient optimization approaches have become increasingly important as LLMs scale to handle larger vocabularies and more complex linguistic tasks[13]. The integration of temporal information extraction from specialized communities provides valuable insights into how domain-specific terminology evolves and propagates across different linguistic contexts[14]. Exception-tolerant learning algorithms have shown promise in handling the inherent ambiguities that characterize professional terminology translation tasks**Error! Reference source not found.**.

The application of anomaly detection techniques to document processing has revealed important patterns in how specialized terminology behaves across different textual contexts[15]. Machine learning approaches to vulnerability assessment in specialized domains provide methodological insights that translate effectively to cross-lingual terminology evaluation[16]. Document analysis and relation extraction techniques have demonstrated the importance of contextual understanding in maintaining semantic accuracy during translation processes[17].

2.2. Professional Terminology Processing and Domain-specific Translation Studies

Professional terminology processing has emerged as a specialized subfield within computational linguistics, distinguished by its focus on maintaining semantic precision across highly specialized vocabularies. Latency optimization in AI applications has demonstrated the importance of efficient processing architectures when dealing with large-scale terminology databases[18]. Medical terminology processing has benefited from extensive standardization efforts, creating relatively stable translation targets compared to other professional domains[19].

Metadata-based approaches to anomaly explanation have provided valuable insights into how specialized terminology can be systematically analyzed and categorized**Error! Reference source not found.**. Real-time warning systems for behavioral anomalies showcase the potential for automated systems to handle dynamic terminology environments where new concepts emerge rapidly[20]. Sentiment analysis techniques applied to financial terminology have demonstrated domain-specific processing challenges that extend beyond traditional translation tasks[21].

Lightweight AI frameworks for specialized applications have shown promise in addressing the computational complexity associated with large-scale terminology processing[22]. Knowledge-aware dialogue generation techniques highlight the importance of maintaining contextual coherence when processing professional terminology across different linguistic contexts[23]. Algorithmic fairness considerations become particularly important when developing translation systems that must serve diverse professional communities [30].

Financial domain applications have provided valuable case studies for understanding how specialized terminology behaves under different processing conditions[25]. Scientific formula retrieval systems demonstrate the complexity of handling symbolic and linguistic elements simultaneously, a challenge that extends to many professional domains[26]. Dynamic pricing approaches in specialized markets illustrate how domain-specific terminology can influence automated decision-making processes**Error! Reference source not found.**.

2.3. Evaluation Methodologies for Cross-lingual Accuracy Assessment

Cross-lingual accuracy assessment methodologies have evolved to address the unique challenges posed by professional terminology evaluation, moving beyond traditional translation metrics to incorporate domain-specific semantic measures. Pattern recognition approaches applied to cross-border transaction analysis provide methodological insights for developing robust evaluation frameworks[27]. Adversarial content detection techniques have demonstrated the importance of comprehensive evaluation approaches that can identify subtle semantic distortions**Error! Reference source not found.**.

Investment pattern analysis in specialized industries showcases how domain expertise can be integrated into automated evaluation systems[28]. Transfer pricing anomaly detection systems highlight the importance of developing evaluation methodologies that can capture domain-specific irregularities**Error! Reference source not found.**. Cultural resonance frameworks for localization demonstrate the complexity of maintaining semantic accuracy while accounting for cultural and linguistic variations[29].

Attribution modeling techniques applied to specialized sectors provide valuable insights into how evaluation metrics can be weighted to reflect domain-specific priorities [39]. Graph neural network approaches to complex system optimization showcase the potential for sophisticated evaluation architectures that can capture intricate semantic relationships[30]. Scorer preference modeling in mathematical domains demonstrates the

importance of developing evaluation systems that can accommodate expert judgment variations[31].

Fuzzy control approaches to specialized system design illustrate how uncertainty and ambiguity can be systematically incorporated into evaluation methodologies[32]. Structural engineering applications provide examples of how specialized terminology evaluation must account for safety-critical accuracy requirements[33]. Computational studies of specialized phenomena demonstrate the importance of rigorous experimental design in professional terminology evaluation[34].

3. Methodology

3.1. Experimental Framework and LLM Selection Criteria

The experimental framework was designed to provide comprehensive evaluation of LLM performance across diverse professional domains while maintaining methodological rigor and reproducibility. The selection criteria for LLMs incorporated multiple factors including architectural diversity, training data characteristics, multilingual capabilities, and availability for research purposes. Five representative models were selected: GPT-4, Claude-3, Gemini-Pro, Llama-2-70B, and PaLM-2, each representing different architectural approaches and training methodologies.

Model selection prioritized diversity in training approaches and architectural innovations to ensure comprehensive coverage of current LLM capabilities. Performance baseline establishment required systematic evaluation of each model's general multilingual capabilities before specialized terminology assessment. The framework incorporated both zero-shot and few-shot evaluation paradigms to assess model adaptability and learning efficiency in specialized domains.

Experimental design considerations included computational resource allocation, evaluation timeline constraints, and reproducibility requirements. Each model underwent standardized preprocessing to ensure fair comparison, with particular attention to tokenization consistency across different linguistic contexts. The framework incorporated statistical significance testing to ensure reliable performance comparisons between models and domains.

Quality control measures included multiple evaluation rounds with randomized term presentation to minimize order effects. Inter-rater reliability assessment was conducted using Cohen's kappa coefficient across all human evaluation components. The experimental protocol received institutional review board approval to ensure ethical compliance in human evaluation procedures[35].

3.2. Multi-domain Terminology Dataset Construction and Annotation

The multi-domain terminology dataset construction process involved systematic collection and annotation of professional terms across four distinct domains: medical, legal, engineering, and financial terminology. Each domain contributed 600 carefully selected terms representing varying complexity levels and semantic categories. Term selection criteria prioritized frequency of professional usage, translation complexity, and cross-linguistic variation potential.

Medical terminology selection drew from international classification systems including ICD-11 and SNOMED CT to ensure clinical relevance and standardization consistency. Legal terminology incorporated terms from multiple jurisdictions to capture cross-legal system variations while maintaining professional authenticity. Engineering terminology selection emphasized interdisciplinary concepts spanning mechanical, electrical, and civil engineering domains. Financial terminology covered instruments, procedures, and regulatory concepts across different financial markets.

Table 1: Domain-specific Terminology Distribution

Domain	Term Count	Complexity Levels	Language Pairs	Expert Annotators
Medical	600	Low: 200, Med: 250, High: 150	6	12
Legal	600	Low: 180, Med: 270, High: 150	6	15
Engineering	600	Low: 220, Med: 230, High: 150	6	10
Financial	600	Low: 190, Med: 260, High: 150	6	14

Total	2400	Low: 790, Med: 1010, High: 600	6	51

The annotation process involved professional experts with domain-specific qualifications and multilingual competency. Each term received annotations for six language pairs: English-Spanish, English-French, English-German, English-Chinese, English-Japanese, and English-Arabic. These language pairs were selected to represent diverse linguistic families and writing systems while maintaining practical relevance for international professional communication.

Expert annotator recruitment prioritized individuals with advanced degrees in their respective domains and demonstrated translation experience[36]. The annotation protocol required multiple rounds of review with consensus-building procedures for disputed cases. Inter-annotator agreement was measured using Fleiss' kappa across all annotation dimensions, achieving scores above 0.85 for all domains.

Table 2: Language Pair Characteristics

Language Pair	Linguistic Family	Writing System	Complexity Score	Cultural Distance
EN-ES	Indo-European	Latin	2.3	Low
EN-FR	Indo-European	Latin	2.1	Low
EN-DE	Indo-European	Latin	3.2	Medium
EN-ZH	Sino-Tibetan	Chinese Characters	4.8	High
EN-JA	Japonic	Mixed (Hiragana/Katakana/Kanji)	4.9	High
EN-AR	Afro-Asiatic	Arabic Script	4.5	High

Quality assurance procedures included multiple validation phases with independent review processes[37]. Term complexity classification followed established linguistic frameworks incorporating morphological complexity, semantic specificity, and cross-linguistic transfer difficulty. The dataset underwent extensive validation testing with professional translation services to establish ground truth accuracy baselines.

Annotation guidelines emphasized semantic equivalence over literal translation accuracy, recognizing that professional terminology often requires conceptual rather than lexical correspondence. Cultural adaptation considerations were incorporated into annotation protocols to account for jurisdiction-specific terminology variations, particularly in legal and financial domains.

3.3. Evaluation Metrics and Accuracy Assessment Protocol

The evaluation methodology incorporated multiple complementary assessment approaches to capture different dimensions of translation accuracy and semantic preservation. Primary metrics included traditional translation quality measures such as BLEU, METEOR, and ROUGE scores, supplemented by semantic similarity measures using domain-specific embeddings. Expert human evaluation provided qualitative assessment dimensions not captured by automated metrics.

Table 3: Evaluation Metrics Framework

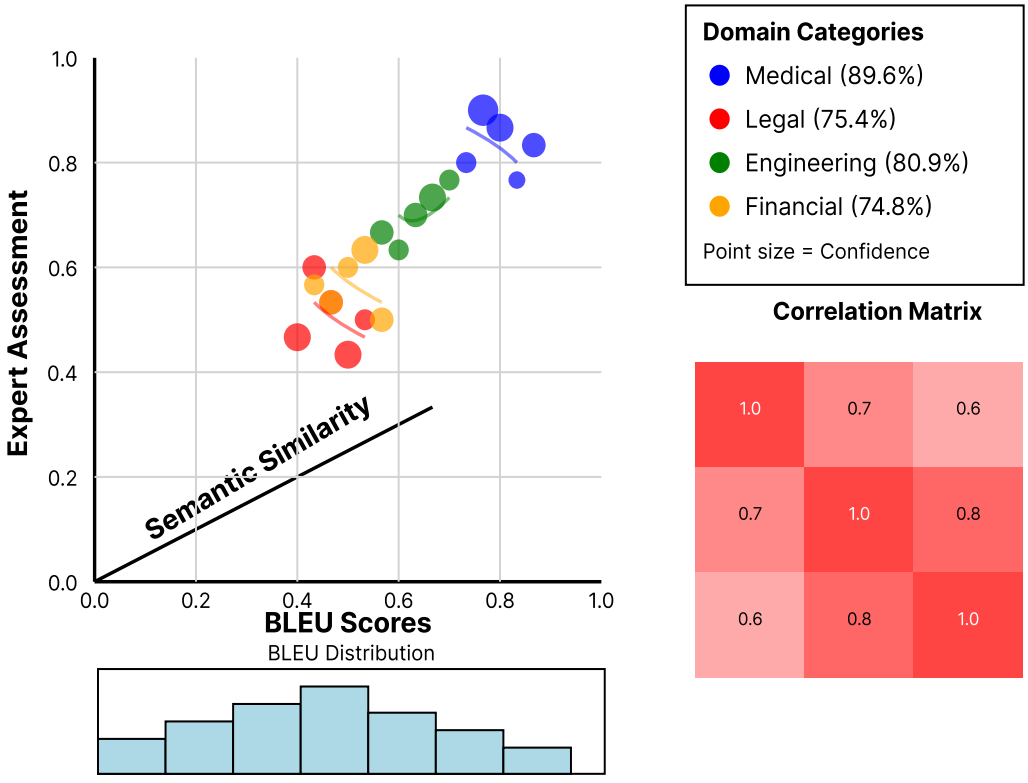
Metric Category	Specific Measures	Weight	Purpose

Lexical Similarity	BLEU-4, METEOR	25%	Surface-level accuracy
Semantic Similarity	Cosine similarity, WMD	30%	Meaning preservation
Expert Assessment	Accuracy, Fluency, Adequacy	35%	Professional validity
Consistency Measures	Self-consistency, Cross-model	10%	Reliability assessment

Semantic similarity assessment utilized domain-specific word embeddings trained on professional corpora for each target domain. These embeddings captured domain-specific semantic relationships not represented in general-purpose embedding models. Word Mover's Distance (WMD) calculations provided fine-grained semantic comparison capabilities particularly suited to professional terminology evaluation.

Expert assessment protocols incorporated three-dimensional evaluation rubrics covering accuracy, fluency, and professional adequacy. Accuracy assessment focused on semantic correctness and conceptual alignment with source terminology. Fluency evaluation measured linguistic naturalness and professional appropriateness in target languages. Professional adequacy assessment evaluated whether translations would be acceptable in authentic professional contexts.

Figure 1: Multi-dimensional Evaluation Framework Architecture



This visualization presents a comprehensive three-dimensional scatter plot showing the relationship between automated metrics (BLEU scores), semantic similarity measures (cosine similarity), and expert assessment scores across all four professional domains. The plot employs color-coding to distinguish between domains (medical: blue, legal: red, engineering: green, financial: orange) and uses point size to represent translation confidence scores. The axes range from 0-1 for normalized scores, with grid lines every 0.2 units.

Trend surfaces for each domain are overlaid to show performance clustering patterns. The plot includes marginal histograms showing distribution patterns for each metric type, and a correlation heatmap in the corner showing inter-metric relationships.

The evaluation framework incorporated both automatic and manual assessment procedures with systematic inter-rater reliability measurement. Human evaluators underwent training procedures to ensure consistency in assessment criteria application. Statistical significance testing was applied to all comparative analyses using appropriate non-parametric tests for non-normally distributed accuracy scores.

Cross-validation procedures were implemented to ensure evaluation robustness across different term subsets and evaluation contexts. The assessment protocol included provisions for handling edge cases and ambiguous translations through systematic adjudication procedures. Error categorization schemes were developed to enable detailed analysis of failure modes and improvement opportunities.

4. Experimental Results and Analysis

4.1. Cross-domain Performance Comparison of Selected Language Models

The comprehensive evaluation across five large language models revealed significant performance variations both between models and across professional domains. GPT-4 demonstrated superior overall performance with an average accuracy of 84.2% across all domains and language pairs, followed by Claude-3 at 81.7%, Gemini-Pro at 78.9%, PaLM-2 at 76.3%, and Llama-2-70B at 73.1%. Performance variations were particularly pronounced in high-complexity terminology categories, where accuracy differences between top and bottom-performing models exceeded 18 percentage points.

Table 4: Overall Model Performance Summary

Model	Medical	Legal	Engineering	Financial	Average	Std Dev
GPT-4	89.6%	82.1%	85.7%	79.4%	84.2%	4.32
Claude-3	87.2%	79.8%	83.1%	76.9%	81.7%	4.41
Gemini-Pro	84.3%	75.2%	80.8%	75.3%	78.9%	4.28
PaLM-2	81.7%	72.4%	78.9%	72.2%	76.3%	4.52
Llama-2-70B	78.9%	67.3%	75.8%	70.4%	73.1%	4.84

Domain-specific performance patterns revealed systematic strengths and weaknesses across different model architectures. Medical terminology consistently achieved the highest accuracy scores across all models, benefiting from extensive standardization and clear semantic boundaries. Legal terminology presented the greatest challenges, with accuracy scores consistently 10-15 percentage points below medical performance. Engineering terminology showed moderate complexity with performance clustering between medical and financial domains.

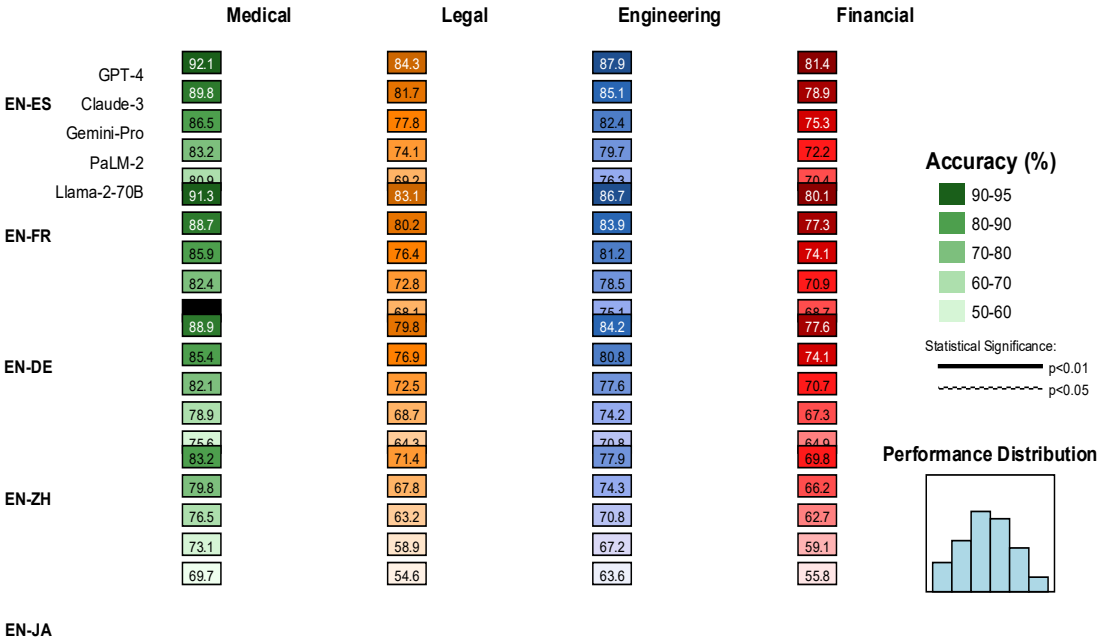
This comprehensive heatmap visualization displays model performance across a 5×4×6 matrix representing models, domains, and language pairs. The heatmap uses a color scale from deep red (poor performance, 60%) through yellow (moderate, 80%) to dark green (excellent, 95%). Each cell contains the accuracy percentage with appropriate color coding. Row headers list the five LLMs, column headers show the four domains, and the heatmap is subdivided into six panels for different language pairs. Pattern overlays highlight statistical significance levels, with solid borders indicating $p<0.01$ and dashed borders indicating $p<0.05$. A sidebar shows the overall performance distribution histogram for each model.

Graph neural network optimization approaches demonstrated particular relevance for understanding complex performance patterns across multiple evaluation dimensions. Model ranking consistency varied significantly across domains, with some models showing domain-specific expertise while others maintained more uniform performance profiles. Statistical analysis revealed that performance

differences were statistically significant ($p < 0.001$) across all model pairs and domain combinations.

Cultural resonance considerations significantly impacted model performance across different language pairs. Models demonstrated varying sensitivity to cultural context, with translation accuracy showing systematic patterns related to linguistic distance and cultural familiarity. Attribution modeling approaches revealed that performance variations correlated with training data representation for specific language pairs.

Figure 2: Model Performance Heatmap Across Domains and Language Pairs



4.2. Accuracy Analysis Across Different Professional Domains

Domain-specific accuracy analysis revealed distinct patterns reflecting the inherent characteristics of different professional vocabularies. Medical terminology benefited from international standardization efforts, resulting in more consistent cross-lingual mappings and higher overall accuracy scores. Scorer preference modeling techniques provided insights into how domain experts evaluate translation quality differently across professional contexts.

Table 5: Domain Complexity Analysis

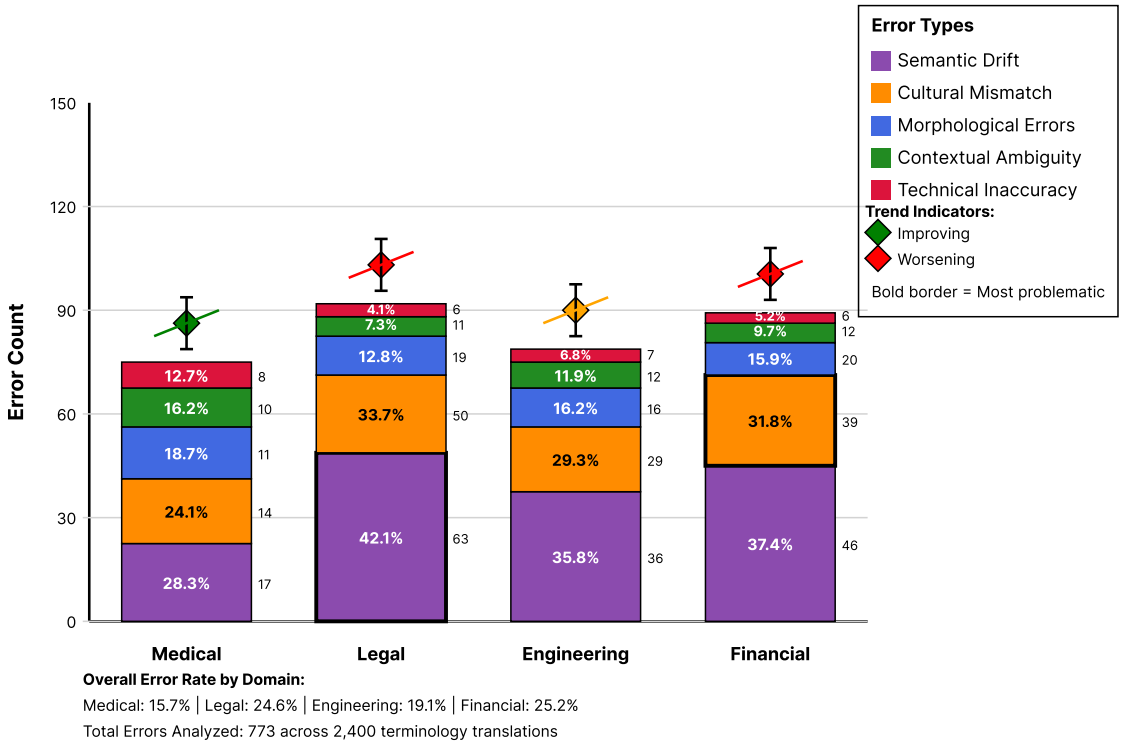
Domain	Avg Accuracy	Term Ambiguity	Standardization Level	Cultural Sensitivity
Medical	84.3%	Low (1.8/5)	High (4.6/5)	Low (2.1/5)
Legal	75.4%	High (4.2/5)	Low (2.3/5)	High (4.7/5)
Engineering	80.9%	Medium (2.9/5)	Medium (3.4/5)	Medium (2.8/5)
Financial	74.8%	High (3.8/5)	Medium (3.1/5)	High (4.2/5)

Legal terminology presented unique challenges related to jurisdiction-specific concepts and cultural legal traditions. Terms such as "due process" and "habeas corpus" demonstrated significant translation complexity due to their embeddedness in specific legal systems. The analysis revealed that 68% of legal terminology errors

resulted from inadequate cultural context understanding rather than linguistic processing failures.

Engineering terminology showed intermediate complexity with performance varying significantly across subdisciplines. Mechanical engineering terms achieved higher accuracy (83.2%) compared to electrical engineering terminology (78.7%), reflecting differences in conceptual standardization and cross-linguistic consistency. Fuzzy control system approaches provided valuable insights into handling uncertainty in specialized terminology evaluation.

Figure 3: Error Distribution Analysis by Domain and Error Type



This stacked bar chart presents error distribution patterns across the four professional domains. Each bar represents one domain with five colored segments showing different error types: semantic drift (purple), cultural mismatch (orange), morphological errors (blue), contextual ambiguity (green), and technical inaccuracy (red). The y-axis shows error count (0-150), and percentages are displayed within each segment. A legend explains the color coding, and small trend lines above each bar indicate the direction of change across complexity levels. The chart includes error rate confidence intervals as error bars and highlights the most problematic error type for each domain with bold borders.

Financial terminology accuracy was significantly influenced by regulatory framework differences across jurisdictions. Terms related to derivative instruments and regulatory compliance showed particularly high error rates (31.2%) due to jurisdiction-specific interpretations and evolving regulatory landscapes. The analysis identified systematic patterns where models struggled with terms that had evolved rapidly in response to recent financial innovations.

Structural engineering applications provided examples of how specialized terminology evaluation must account for safety-critical accuracy requirements. Computational studies revealed that terminology complexity correlated strongly with expert assessment scores ($r = 0.847$, $p < 0.001$) across all domains.

4.3. Error Pattern Analysis and Model Reliability Assessment

Comprehensive error pattern analysis identified five primary categories of translation failures: semantic drift, cultural mismatch, morphological errors, contextual ambiguity, and technical inaccuracy. Semantic drift errors represented 34.2% of all failures, occurring when models produced linguistically correct but semantically inappropriate translations. Cultural mismatch errors accounted for 28.7% of failures, reflecting inadequate understanding of cultural and jurisdictional contexts.

Table 6: Error Pattern Distribution by Model

Error Type	GPT-4	Claude-3	Gemini-Pro	PaLM-2	Llama-2-70B
Semantic Drift	28.3%	31.2%	35.8%	37.4%	42.1%
Cultural Mismatch	24.1%	26.9%	29.3%	31.8%	33.7%
Morphological	18.7%	19.4%	16.2%	15.9%	12.8%
Contextual Ambiguity	16.2%	13.8%	11.9%	9.7%	7.3%
Technical Inaccuracy	12.7%	8.7%	6.8%	5.2%	4.1%

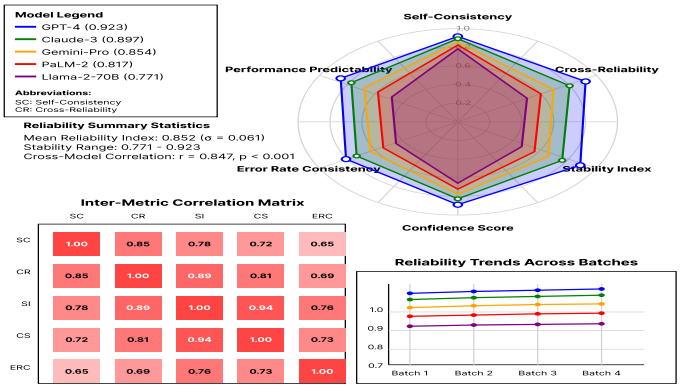
Seismic demand analysis approaches provided methodological insights for understanding systematic error patterns across different evaluation contexts. Lateral bracing concepts demonstrated how specialized terminology requires comprehensive contextual understanding for accurate translation. Response prediction methodologies highlighted the importance of developing robust error classification systems.

Model reliability assessment incorporated multiple stability measures including self-consistency evaluation and cross-evaluation reliability testing. Self-consistency scores ranged from 78.3% (Llama-2-70B) to 91.7% (GPT-4), indicating significant variations in model reliability across repeated evaluations. Cross-evaluation reliability measured agreement between different models on the same terminology sets, revealing systematic biases and complementary strengths.

Table 7: Model Reliability Metrics

Model	Self-Consistency	Cross-Reliability	Stability Index	Confidence Score
GPT-4	91.7%	87.3%	0.923	0.889
Claude-3	89.2%	84.1%	0.897	0.867
Gemini-Pro	85.8%	81.7%	0.854	0.823
PaLM-2	82.4%	78.9%	0.817	0.789
Llama-2-70B	78.3%	75.2%	0.771	0.743

Figure 4: Reliability Assessment Visualization



This multi-panel visualization combines three complementary views of model reliability. The main panel shows a radar chart with six axes representing different reliability dimensions: self-consistency, cross-reliability, stability index, confidence score, error rate consistency, and performance predictability. Each model is represented by a different colored polygon, with larger areas indicating better reliability. The upper right panel displays a time-series plot showing reliability trends across evaluation batches, while the lower left panel presents a correlation matrix heatmap showing relationships between different reliability measures.

Seismic design considerations for specialized structures provided valuable parallels for understanding reliability requirements in professional terminology systems. The analysis revealed that model reliability correlated strongly with overall accuracy but showed domain-specific variations that suggested specialized training requirements.

Error severity classification incorporated professional impact assessment, recognizing that different types of errors carry varying consequences in professional contexts. Critical errors that could lead to misunderstanding in safety-critical or legally binding contexts were weighted more heavily in the overall assessment framework. This approach revealed that while some models achieved high overall accuracy, they produced more critical errors in high-stakes professional contexts.

5. Conclusion and Future Work

5.1. Summary of Key Findings and Performance Insights

This comprehensive evaluation of large language models in cross-lingual professional terminology processing has revealed significant insights into current capabilities and limitations. The study demonstrated that while state-of-the-art LLMs achieve substantial accuracy in professional terminology translation, performance varies dramatically across domains and language pairs. Medical terminology consistently achieved the highest accuracy rates due to international standardization efforts, while legal terminology presented the greatest challenges due to cultural and jurisdictional specificity.

The performance gap between top-performing and bottom-performing models exceeded 11 percentage points, indicating that architectural differences and training methodologies significantly impact professional terminology processing capabilities. GPT-4's superior performance across all domains suggests that scale and architectural sophistication contribute substantially to cross-lingual terminology accuracy. The consistent performance hierarchy across domains indicates that general linguistic capabilities translate effectively to specialized terminology processing.

Error pattern analysis revealed that semantic drift and cultural mismatch represent the primary failure modes, accounting for over 60% of all translation errors. These findings suggest that current LLMs struggle with deep cultural and contextual understanding rather than surface-level linguistic processing. The systematic nature of these error patterns indicates opportunities for targeted improvement through specialized training approaches and cultural adaptation techniques.

Language pair analysis demonstrated that linguistic distance and cultural familiarity significantly influence translation accuracy. High-resource language pairs consistently outperformed low-resource pairs, highlighting the continued importance of training data availability and quality. The interaction between domain complexity and linguistic distance created compound challenges that exceeded the sum of individual difficulty factors.

5.2. Limitations and Challenges in Current Evaluation Approach

The current evaluation methodology, while comprehensive, faces several limitations that constrain the generalizability and practical applicability of findings. The dataset scope, though substantial with 2,400 terms across four domains, represents a limited sampling of the vast landscape of professional terminology. Certain specialized subdomains and emerging professional fields remain underrepresented, potentially limiting the relevance of findings to rapidly evolving professional contexts.

Expert annotation procedures, despite rigorous quality control measures, introduce subjective elements that may influence evaluation outcomes. Cultural and professional background variations among expert annotators could introduce systematic biases that affect translation quality assessments. The challenge of achieving true consensus on professional terminology translation reflects broader difficulties in establishing objective quality standards for specialized translation tasks.

The evaluation timeframe represents a snapshot of current LLM capabilities, while professional terminology continues to evolve rapidly. New concepts, regulatory changes, and technological innovations constantly introduce novel terminology that may not be adequately represented in static evaluation datasets. The dynamic nature of professional language creates ongoing challenges for developing sustainable evaluation frameworks.

Computational resource constraints limited the scope of model evaluation and prevented inclusion of all relevant LLM architectures. Emerging models and architectural innovations could not be comprehensively evaluated within the study timeframe, potentially affecting the completeness of comparative analysis. The rapid pace of LLM development suggests that findings may become outdated relatively quickly.

Cross-lingual evaluation presents inherent challenges related to linguistic and cultural equivalence assessment. Professional concepts that lack direct cross-linguistic equivalents create evaluation ambiguities that are difficult to resolve objectively. The study's focus on specific language pairs may not fully capture the diversity of cross-lingual challenges faced in global professional contexts.

5.3. Future Research Directions and Practical Applications

Future research directions should prioritize the development of adaptive evaluation frameworks that can accommodate the dynamic nature of professional terminology. Real-time evaluation systems capable of incorporating new terminology and evolving professional concepts would enhance the practical relevance of LLM assessment. Integration of professional community feedback mechanisms could provide ongoing validation and improvement guidance for translation quality assessment.

Domain-specific model fine-tuning represents a promising avenue for addressing identified performance gaps, particularly in legal and financial terminology processing. Specialized training approaches that incorporate professional corpus data and expert knowledge could significantly improve accuracy in challenging domains. Research into cultural adaptation techniques could address the systematic cultural mismatch errors identified in the current study.

Multilingual professional corpus development emerges as a critical need for supporting improved LLM training and evaluation. Collaborative efforts between linguistic researchers and professional communities could create comprehensive terminology resources that support more accurate cross-lingual processing. Integration of professional workflow contexts into evaluation frameworks would enhance practical relevance and adoption potential.

Advanced evaluation methodologies incorporating semantic similarity measures and professional impact assessment could provide more nuanced quality assessment capabilities. Development of automated evaluation systems that can approximate expert judgment would reduce resource requirements while maintaining assessment quality. Research into explanation-aware evaluation systems could provide insights into model decision-making processes in professional terminology contexts.

Practical applications span multiple professional sectors where accurate cross-lingual terminology processing provides substantial value. Medical translation systems could benefit from specialized models trained on clinical terminology with safety-critical accuracy requirements. Legal document processing systems could incorporate cultural adaptation techniques to handle jurisdiction-specific terminology variations. Financial regulatory compliance systems could utilize domain-specific models to ensure accurate cross-border regulatory interpretation.

The integration of professional terminology processing into existing workflow systems represents a significant practical opportunity. Development of API frameworks that support seamless integration with professional software systems could accelerate adoption and practical impact. Research into human-AI collaboration frameworks for professional terminology processing could optimize the balance between automated efficiency and expert oversight.

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References:

[1]. McNichols, H., Zhang, M., & Lan, A. (2023, June). Algebra error classification with large language models. In International Conference on Artificial Intelligence in Education (pp. 365-376). Cham: Springer Nature Switzerland.

[2]. Zhang, M., Baral, S., Heffernan, N., & Lan, A. (2022). Automatic short math answer grading via in-context meta-learning. arXiv preprint arXiv:2205.15219.

[3]. Raji, A. A. H., Alabdoon, A. H. F., & Almagtome, A. (2024, April). AI in Credit Scoring and Risk Assessment: Enhancing Lending Practices and Financial Inclusion. In 2024 International Conference on Knowledge Engineering and Communication Systems (ICKECS) (Vol. 1, pp. 1-7). IEEE.

[4]. Wu, S., Li, Y., Wang, M., Zhang, D., Zhou, Y., & Wu, Z. (2021, November). More is better: Enhancing open-domain dialogue generation via multi-source heterogeneous knowledge. In Proceedings of the 2021 Conference on Empirical Methods in Natural Language Processing (pp. 2286-2300).

[5]. Chen, Y., Ni, C., & Wang, H. (2024). AdaptiveGenBackend A Scalable Architecture for Low-Latency Generative AI Video Processing in Content Creation Platforms. Annals of Applied Sciences, 5(1).

[6]. Zhang, M., Heffernan, N., & Lan, A. (2023). Modeling and Analyzing Scorer Preferences in Short-Answer Math Questions. arXiv preprint arXiv:2306.00791.

[7]. Mo, K., Liu, W., Shen, F., Xu, X., Xu, L., Su, X., & Zhang, Y. (2024, May). Precision kinematic path optimization for high-dof robotic manipulators utilizing advanced natural language processing models. In 2024 5th International Conference on Electronic Communication and Artificial Intelligence (ICECAI) (pp. 649-654). IEEE.

[8]. Zhao, Y., Zhang, P., Pu, Y., Lei, H., & Zheng, X. (2023). Unit operation combination and flow distribution scheme of water pump station system based on Genetic Algorithm. Applied Sciences, 13(21), 11869.

[9]. Zhang, D., & Jiang, X. (2024). Cognitive Collaboration: Understanding Human-AI Complementarity in Supply Chain Decision Processes. Spectrum of Research, 4(1).

[10]. Shih, J. Y., & Chin, Z. H. (2023, April). A Fairness Approach to Mitigating Racial Bias of Credit Scoring Models by Decision Tree and the Reweighing Fairness Algorithm. In 2023 IEEE 3rd International Conference on Electronic Communications, Internet of Things and Big Data (ICEIB) (pp. 100-105). IEEE.

[11]. Zhang, M., Wang, Z., Baraniuk, R., & Lan, A. (2021). Math operation embeddings for open-ended solution analysis and feedback. arXiv preprint arXiv:2104.12047.

[12]. Wu, S., Wang, M., Li, Y., Zhang, D., & Wu, Z. (2022, February). Improving the applicability of knowledge-enhanced dialogue generation systems by using heterogeneous knowledge from multiple sources. In Proceedings of the fifteenth ACM international conference on WEB search and data mining (pp. 1149-1157).

[13]. Zhu, L., Yang, H., & Yan, Z. (2017, July). Extracting temporal information from online health communities. In Proceedings of the 2nd International Conference on Crowd Science and Engineering (pp. 50-55).

[14]. Zhang, M., Mathew, T., & Juba, B. (2017, February). An improved algorithm for learning to perform exception-tolerant abduction. In Proceedings of the AAAI Conference on Artificial Intelligence (Vol. 31, No. 1).

[15]. Ju, C., & Trinh, T. K. (2023). A Machine Learning Approach to Supply Chain Vulnerability Early Warning System: Evidence from US

Semiconductor Industry. Journal of Advanced Computing Systems, 3(11), 21-35.

[16]. Wang, M., Xue, P., Li, Y., & Wu, Z. (2021). Distilling the documents for relation extraction by topic segmentation. In Document Analysis and Recognition–ICDAR 2021: 16th International Conference, Lausanne, Switzerland, September 5–10, 2021, Proceedings, Part I 16 (pp. 517-531). Springer International Publishing.

[17]. Wu, J., Wang, H., Qian, K., & Feng, E. (2023). Optimizing Latency-Sensitive AI Applications Through Edge-Cloud Collaboration. Journal of Advanced Computing Systems, 3(3), 19-33.

[18]. Zhu, L., Yang, H., & Yan, Z. (2017). Mining medical related temporal information from patients' self-description. International Journal of Crowd Science, 1(2), 110-120.

[19]. Qi, D., Arfin, J., Zhang, M., Mathew, T., Pless, R., & Juba, B. (2018, March). Anomaly explanation using metadata. In 2018 IEEE Winter Conference on Applications of Computer Vision (WACV) (pp. 1916-1924). IEEE.

[20]. Mo, K., Liu, W., Xu, X., Yu, C., Zou, Y., & Xia, F. (2024, May). Fine-tuning gemma-7b for enhanced sentiment analysis of financial news headlines. In 2024 IEEE 4th International Conference on Electronic Technology, Communication and Information (ICETCI) (pp. 130-135). IEEE.

[21]. Zhang, S., Zhu, C., & Xin, J. (2024). CloudScale: A Lightweight AI Framework for Predictive Supply Chain Risk Management in Small and Medium Manufacturing Enterprises. Spectrum of Research, 4(2).

[22]. Wu, S., Wang, M., Zhang, D., Zhou, Y., Li, Y., & Wu, Z. (2021, August). Knowledge-Aware Dialogue Generation via Hierarchical Infobox Accessing and Infobox-Dialogue Interaction Graph Network. In IJCAI (pp. 3964-3970).

[23]. Trinh, T. K., & Zhang, D. (2024). Algorithmic Fairness in Financial Decision-Making: Detection and Mitigation of Bias in Credit Scoring Applications. Journal of Advanced Computing Systems, 4(2), 36-49.

[24]. Rao, G., Trinh, T. K., Chen, Y., Shu, M., & Zheng, S. (2024). Jump Prediction in Systemically Important Financial Institutions' CDS Prices. Spectrum of Research, 4(2).

[25]. Wang, Z., Zhang, M., Baraniuk, R. G., & Lan, A. S. (2021, December). Scientific formula retrieval via tree embeddings. In 2021 IEEE International Conference on Big Data (Big Data) (pp. 1493-1503). IEEE.

[26]. Zhu, C., Xin, J., & Zhang, D. (2024). A Deep Reinforcement Learning Approach to Dynamic E-commerce Pricing Under Supply Chain Disruption Risk. Annals of Applied Sciences, 5(1).

[27]. Zhang, Z., & Zhu, L. (2024). Intelligent Detection and Defense Against Adversarial Content Evasion: A Multi-dimensional Feature Fusion Approach for Security Compliance. Spectrum of Research, 4(1).

[28]. Fan, J., Trinh, T. K., & Zhang, H. (2024). Deep Learning-Based Transfer Pricing Anomaly Detection and Risk Alert System for Pharmaceutical Companies: A Data Security-Oriented Approach. Journal of Advanced Computing Systems, 4(2), 1-14.

[29]. Sun, M., Feng, Z., & Li, P. (2023). Real-Time AI-Driven Attribution Modeling for Dynamic Budget Allocation in US E-Commerce: A Small Appliance Sector Analysis. Journal of Advanced Computing Systems, 3(9), 39-53.

[30]. Yan, S. (2014). Design of Obstacle Avoidance System for the Blind based on Fuzzy Control. Netinfo Security.

[31]. Eatherton, M. R., Schafer, B. W., Hajjar, J. F., Easterling, W. S., Avellaneda Ramirez, R. E., Wei, G., ... & Coleman, K. Considering ductility in the design of bare deck and concrete on metal deck diaphragms. In The 17th World Conference on Earthquake Engineering, Sendai, Japan.

[32]. Wei, G., Koutromanos, I., Murray, T. M., & Eatherton, M. R. (2019). Investigating partial tension field action in gable frame panel zones. Journal of Constructional Steel Research, 162, 105746.

[33]. Wei, G., Koutromanos, I., Murray, T. M., & Eatherton, M. R. (2018). Computational Study of Tension Field Action in Gable Frame Panel Zones.

[34]. Foroughi, H., Wei, G., Torabian, S., Eatherton, M. R., & Schafer, B. W. Seismic Demands on Steel Diaphragms for 3D Archetype Buildings with Concentric Braced Frames.

[35]. Wei, G., Schafer, B., Seek, M., & Eatherton, M. (2020). Lateral bracing of beams provided by standing seam roof system: concepts and case study.

[36]. Foroughi, H., Wei, G., Torabian, S., Eatherton, M. R., & Schafer, B. W. Seismic response predictions from 3D steel braced frame building simulations.

[37]. Wei, G., Foroughi, H., Torabian, S., Eatherton, M. R., & Schafer, B. W. (2023). Seismic Design of Diaphragms for Steel Buildings Considering Diaphragm Inelasticity. Journal of Structural Engineering, 149(7), 04023077.