A Multi-Language NLP Model for Inclusive Digital Healthcare Marketing and Patient Communication

Nargis Parveen
Department of Computer Sciences, Faculty of Computing and Information Technology, Northern Border University, Rafha, Saudi Arabia
nargis.norulhaq@nbu.edu.sa

Albia Maqbool
Department of Computer Sciences, Faculty of Computing and Information Technology, Northern Border University, Rafha, Saudi Arabia
albia.alam@nbu.edu.sa (corresponding author)

Hina Skhawat
Department of Basic Sciences, Applied College, Northern Border University, Saudi Arabia
hina.skhawat@nbu.edu.sa

Rima Osama Mohammad Othman
Department of Administrative Sciences, Applied College, Northern Border University, Saudi Arabia
rema.mohammad@nbu.edu.sa

Dima Mahmoud Aref Abbadi
Department of Administrative Sciences, Faculty of Applied College, Northern Border University, Saudi Arabia
dema.abadi@nbu.edu.sa

Esraa M. Al-Lobani
Department of Mathematics Sciences, Faculty of Applied College, Northern Border University, Saudi Arabia
esraa.khaled@nbu.edu.sa

Shama Mashhour M. Alqahtani
Department of Basic Sciences, Applied College, Northern Border University, Saudi Arabia
shama.alqahtani@nbu.edu.sa

Muhammad Skhawat Ali
Department of Basic Sciences, Applied College, Northern Border University, Saudi Arabia
mohammed.moneer@nbu.edu.sa

Khaled Mejdi
Department of Administrative sciences, Applied College, Northern Border University, Rafha, Saudi Arabia
khaled.mejdi@nbu.edu.sa

Wassim Zahrouni
Department of Finance and Insurance, College of Business Administration, Northern Border University, Saudi Arabia
wassim.zahrouni@nbu.edu.sa

Received: 2 November 2024 | Revised: 5 December 2024, 16 December 2024, and 23 December 2024 | Accepted: 29 December 2024

 DOI: https://doi.org/10.48084/etasr.9484

ABSTRACT

Digital healthcare systems integrate Natural Language Processing (NLP) to make advances in the ways patients engage and communicate. However, multilingual access to a wide variety of languages has been an ongoing problem. This study introduces a multilingual NLP model for digital healthcare marketing and patient communication, designed to help patients obtain health information across languages. This work addresses essential multilingual issues in the healthcare context, such as providing a language-adaptive function using state-of-the-art semantic processing. The model introduces linguistic diversity for personalized healthcare marketing to help develop more personal relationships with patients. The model was evaluated across languages to determine whether it provides practical benefits in enabling clear and culturally attuned communication. This model has the potential to help create a linguistically inclusive healthcare environment, helping patients understand their health conditions and treatment options, and increasing overall patient satisfaction.

Keywords-natural language processing; multi-language model; digital healthcare marketing; patient communication; inclusivity; language adaptation; healthcare management

I. INTRODUCTION

The language barrier remains a significant challenge in digital healthcare communication [1, 2]. NLP has come a long way in assisting healthcare conversations, but most systems do not support multiple languages, which can be a problem for inclusiveness. Current models are likely to perform poorly in large-scale multilingual applications since they prioritize English. This study seeks to address these concerns by creating a multi-language NLP model to address the linguistic divide with the aim of: (i) properly cross-translate in medical contexts, (ii) better connecting through culturally sensitive information dissemination, and (iii) ultimately improving patient-centered communication across various languages [3]. In the healthcare field, NLP is used to help patients ask questions and analyze records, but it still encompasses a variety of disadvantages, especially in multilingual contexts [4]. Although recent models support cross-linguistic patient care, they often fall short in terms of the accuracy and cultural appropriateness necessary for nuanced healthcare communication. [5, 6]. This trend to cater to diverse patient needs regarding inclusive communication has called for the development of adaptive language models [4]. The inability of current NLP models to deliver culturally interpretable results has been emphasized along with other language-qualified metrics in multicultural healthcare [7-9]. Existing multilingual NLP models, such as multilingual BERT and XLM-RoBERTa, have advanced cross-lingual capabilities in general domains [5, 6]. However, their application to healthcare contexts reveals critical gaps, including the inability to address domain-specific terminology and cultural nuances. Although these models perform well for generic translation tasks, they lack the contextual precision required for accurate medical communication [1, 5]. Furthermore, most of these works do not incorporate dialectal variations or medical ontologies, which are essential for healthcare communication across diverse linguistic groups.

This study introduces a novel approach by integrating:

- Domain-specific training: Utilizes healthcare-focused datasets, such as MIMIC-III [10] and the Chinese Medical Knowledge Database [11], to fine-tune the model for clinical and healthcare-related texts.
- Medical ontology alignment: Leverages resources such as SNOMED CT and UMLS to standardize medical terminology across multiple languages [6, 9].
- Cultural adaptation: Uses metrics to evaluate and ensure cultural sensitivity in multilingual patient communication, a feature absent in current models [5, 12].

This innovative framework bridges existing gaps by providing a scalable, linguistically adaptive, and contextually accurate model for healthcare applications. It not only enhances translation accuracy but also ensures semantic preservation and cultural alignment, positioning it as a significant contribution to multilingual healthcare NLP.

II. METHODOLOGY

This study utilized a hybrid method that combines quantitative and qualitative approaches. The quantitative aspect focuses on model training and performance evaluation using multilingual healthcare datasets, while the qualitative component assesses cultural and linguistic relevance to ensure inclusivity. This framework is designed to bridge linguistic gaps and address challenges in semantic and contextual accuracy in healthcare communication. The proposed method includes the following key steps.

A. Research Design and Framework

The quantitative aspect involves model training and performance evaluation using multilingual healthcare data. The qualitative component evaluates the cultural and linguistic relevance of the model outputs to ensure inclusivity. The framework follows an iterative development cycle of data preparation, model customization, training, validation, and performance evaluation.

1) Expert Demographics

- English: 5 professionals (3 doctors, 2 linguists).
- Spanish: 4 professionals (2 medical translators, 2 linguists).
- Mandarin: 3 professionals (1 doctor, 2 translators).
- French: 4 professionals (2 linguists, 2 healthcare specialists).

These experts reviewed outputs for cultural relevance, linguistic accuracy, and medical validity.

2) Qualitative Analysis Details

- Sample size: 1,000 sentences.
- Criteria: Clarity, accuracy, cultural relevance.
- Reviewers: 10 experts (linguists and healthcare professionals).

B. Dataset Description and Preprocessing Techniques

The model used publicly available multilingual healthcare datasets sourced from reputable databases in English, Spanish, Mandarin, and French to simulate real-world scenarios. Table I outlines the dataset characteristics, including language distribution, total data points, and key attributes.

TABLE I. DATASET CHARACTERISTICS

Language	Dataset source	Data points	Content-type
English	MIMIC-III [10]	1M+	Clinical notes, EHR data, demographics
Spanish	CoWeSe [11]	500K+	Patient instructions, medical reports
Mandarin	TCMD [13]	400K+	Medical descriptions
French	QUAERO [14]	300K+	Healthcare guidelines

- MIMIC-III (English) is a comprehensive critical care database containing over one million de-identified clinical records from intensive care units in the United States. It includes patient demographics, vital signs, laboratory results, and clinical notes, making it a valuable resource for NLP in healthcare [10].
- CoWeSe (Corpus Web Salud Español) is the largest Spanish biomedical corpus to date, consisting of approximately 4.5 GB of clean plain text, equivalent to about 750 million tokens. Compiled in 2020 through extensive web crawling of 3,000 Spanish domains, it serves as a crucial resource for training domain-specific language models and generating word embeddings in the Spanish biomedical field [11].
- Traditional Chinese Medical Database (TCMD) (Mandarin): The TCMD-2013-Eng is an expanded English version of the Traditional Chinese Medical Database, encompassing detailed data and standard specifications of numerous traditional Chinese medicines. It facilitates research and development of new drugs and modern studies on the efficacy and mechanisms of traditional Chinese medicines [13].
- QUAERO French Medical Corpus: The QUAERO project provides a corpus of French biomedical texts annotated at the entity and concept levels. It covers diverse text genres and includes annotations mapped to UMLS concepts, making it valuable for biomedical NLP research [14].

Preprocessing involved data cleaning, tokenization, language-specific normalization, and removal of medical jargon inconsistencies. Stop words, punctuation, and non-essential symbols were filtered to standardize the text for NLP processing. For accurate tokenization, specific language rules were applied, especially for non-Latin scripts, such as segmentation techniques for Mandarin.

C. NLP Model Architecture for Multi-Language Processing

The architecture of the NLP model is based on a transformer framework, specifically optimized for multilingual healthcare communication.

- Encoder layers: The model employs 12 encoder layers, each comprising multi-head self-attention mechanisms and feed-forward networks. This ensures contextual understanding across diverse languages, crucial for preserving medical semantics.
- Attention mechanism: The self-attention mechanism incorporates 8 attention heads, allowing the model to focus on different parts of the input simultaneously. This is particularly effective for understanding long medical sentences with complex terminologies.
- Embedding Dimensions: Each token is represented in a 768-dimensional space, capturing linguistic and semantic features. The embeddings are fine-tuned on domain-specific datasets to enhance contextual accuracy.
- Tokenization Process: A custom tokenization strategy is implemented to handle language-specific nuances. For non-Latin scripts, such as Mandarin, segmentation techniques were used to tokenize text appropriately. For Latin-based languages, subword units were employed to manage rare and compound medical terms.
- Position encoding: To preserve the order of words, positional encodings are added to the input embeddings, enabling the model to distinguish between identical terms in different contexts.
- Domain-specific layers: Additional layers are integrated to address domain-specific requirements, such as recognizing medical abbreviations and standardizing terminologies. These layers use ontologies such as SNOMED CT and UMLS to ensure consistent mapping across languages.
- Output layer: The final layer generates language-specific probabilities for token prediction, adjusted to maintain high translation accuracy and semantic relevance. This layer is optimized using cross-entropy loss to minimize translation errors.

Tailoring the transformer model with these features provides a robust multilanguage NLP architecture capable of delivering high accuracy, semantic preservation, and cultural sensitivity in medical translations. The architecture is based on a transformer model tailored for multilanguage processing, allowing seamless adaptation across diverse languages. The transformer model was selected for its high accuracy in translation and contextual understanding, which is essential for handling medical terminology effectively. The medical term recognition module consists of:

- Input: Preprocessed multilingual data.
- Rule-based methods: Lexicon matching with SNOMED CT and UMLS.
- ML component: Fine-tuned BERT for ambiguous terms.
- Output: Standardized medical terms across languages for consistency.

1) Language-Specific Adaptations

To improve performance, the model integrates language-specific embeddings, optimizing accuracy for each target language. This includes word vector training with monolingual corpora and cross-lingual embeddings for languages with fewer healthcare resources. Table II summarizes language-specific adjustments applied in the model.

TABLE II. LANGUAGE-SPECIFIC ADAPTATIONS

	Embedding technique	Additional adaptation
English	BERT-based embeddings	Enhanced for clinical text
Spanish	Spanish RoBERTa embeddings	Adjusted for dialects
Mandarin	Multilingual BERT embeddings	Segmentation adjustments
French	CamemBERT embeddings	Customized for medical use

2) Customization for Medical Terminology and Semantics

Medical terminology often includes specialized words and abbreviations. A medical term recognition algorithm was implemented to identify and standardize terms across languages. The algorithm incorporates medical ontologies such as SNOMED CT and UMLS to provide accurate term mapping, enhancing semantic understanding in translations [15].

D. Training and Validation Procedures

Three key metrics were used to evaluate performance.

- Translation accuracy was measured using BLEU and METEOR scores, comparing generated translations against expert-annotated references. Accuracy thresholds were set at ≥90%.

$$BLEU = BP \cdot exp(n = 1 \sum N w_n \cdot log p_n)$$

where BP is the brevity penalty, w_n are weights, and p_n is the precision for n-gram matching.

- Semantic relevance was assessed by aligning key medical terms in translations with SNOMED CT and UMLS ontologies, ensuring the preservation of domain-specific meaning.

$$SemanticRelevance = \frac{TotalKeyTerms}{MatchedTerms} \times 100$$

- Cultural sensitivity was evaluated through expert reviews, considering tone, formality, and context suitability across languages. Native speakers scored outputs on a 5-point scale, with a threshold of ≥80%.

$$CulturalSensitivity = \frac{CulturallyAppropriateTranslations}{TotalTranslations} \times 100$$

Model training was carried out using 80% of the dataset, with the remaining 20% reserved for validation. Training cycles involved fine-tuning pre-trained models, specifically BERT and its variants, for multilingual contexts. Validation included evaluating translation accuracy, semantic relevance, and cultural appropriateness. Table III presents performance metrics and thresholds established during the validation.

TABLE III. PERFORMANCE METRICS AND VALIDATION CRITERIA

Metric	Threshold	Description
Translation accuracy	≥90%	Measures correct language outputs
Semantic relevance	≥85%	Ensures context preservation
Cultural sensitivity	≥80%	Validates adaptation to nuances

E. Tools and Software Used for Model Development

Model development utilized Python-based NLP libraries, including Hugging Face's Transformers for model customization and NLTK for data preprocessing. TensorFlow and PyTorch were employed, facilitating efficient model training and validation. Additional software included the UMLS toolkit for medical terminology standardization and spaCy for text parsing and tokenization.

F. Algorithm for Multi-Language NLP Model Training and Adaptation

The following algorithm outlines the systematic approach taken to train and adapt the NLP model for multilingual healthcare communication.

```
Algorithm 1: Multi-Language NLP Model
  Training and Adaptation for Healthcare
Input: Multilingual Healthcare Dataset
  (languages: English, Spanish, Mandarin,
   French)
Output: Optimized MultiLanguage NLP Model
  for Digital Healthcare Communication
1: Initialize Model Architecture
   Load the transformer-based model
   architecture (e.g., BERT, Roberta)
   suitable for multilingual text
   processing.
2: Data Preprocessing
   For each language in the dataset:
```

```
    Tokenize text based on language-
    specific rules.
    Remove stop words, punctuation, and
    symbols.
    Apply normalization (e.g., lowercase
    conversion, stemming).
    Map medical terminology using medical
    ontologies (SNOMED CT, UMLS).
3: Embedding Generation
   For each language:
    Generate language-specific embeddings
    using pre-trained models (e.g., BERT
    for English, CamemBERT for French).
    For languages with fewer resources,
    apply cross-lingual embeddings to
    enhance semantic understanding.
4: Model Customization for Medical Context
   Integrate medical term recognition
   module
   Identify and standardize key terms
   using domain-specific ontologies.
   Adjust the embedding layer for
   healthcare-related semantics.
5: Training phase
   Split dataset:
   80% training, 20% validation.
   For each epoch:
    Fine-tune pre-trained language model
    using language-specific data.
     Calculate translation accuracy,
     semantic relevance, and cultural
     sensitivity.
6: Validation and performance evaluation
   Measure model performance:
   Translation accuracy: Compare
   translations against reference outputs.
   Semantic relevance: Ensure medical
   context is preserved.
   Cultural sensitivity: Assess adaptation
   for cultural nuances.
   If performance thresholds (e.g., ≥90%
   accuracy) are met, proceed;
   Otherwise, adjust model parameters and
   repeat training.
7: Model output and storage
   Store final multi-language NLP model.
   Document model parameters and training
   configurations for reproducibility.
8: End
```

1) Transformer-Based Architecture

The model employs a transformer architecture optimized for multilingual processing. It consists of 12 encoder layers with 8 attention heads per layer, enabling parallel text processing. Positional encodings and multihead attention enhance contextual understanding, essential for preserving the semantics of medical terminology. The architecture incorporates domain-specific layers for medical text adaptation.

2) Language-Specific Rules for Tokenization

Tokenization was tailored for each target language to handle linguistic diversity:

- English and Spanish: Subword-based tokenization (e.g., byte-pair encoding) ensures accurate handling of rare medical terms and compound words.
- Mandarin: Character segmentation methods were applied to accommodate non-alphabetic scripts.
- French: Morphological analysis was used to tokenize complex conjugations and medical phrases. This customized approach reduced errors in token segmentation and improved input quality.

3) Mapping Medical Terminology Using Medical Ontologies

Medical ontologies, including SNOMED CT and UMLS, were integrated to standardize terminology across languages. This process involved:

- Identifying key terms in source text using term-recognition algorithms.
- Mapping these terms to ontology entries to ensure semantic consistency.
- Storing mapped terms in a structured format to enhance cross-lingual semantic alignment.

4) Cross-Lingual Medical Embeddings for Enhanced Semantic Understanding

Pre-trained multilingual embeddings (e.g. multilingual BERT) were fine-tuned on medical datasets. Key steps included:

- Training on aligned bilingual corpora to ensure semantic consistency.
- Applying cross-lingual embeddings to link similar concepts in different languages improves translation accuracy for medical contexts.
- Using embedding to resolve ambiguity in domain-specific terms.

5) Integration of Medical Term Recognition Module

A specialized module was developed to identify and normalize medical terms during processing.

- Recognition: The module uses a rule-based approach augmented with machine learning to detect medical terms.
- Normalization: Terms are aligned with entries in SNOMED CT and UMLS for standardization.
- Application: The module operates within the transformer architecture, ensuring real-time recognition and accurate representation of terms across languages.

Combining these methods allowed the model to achieve robust multilingual capabilities, preserve medical semantics, and ensure culturally relevant translations.

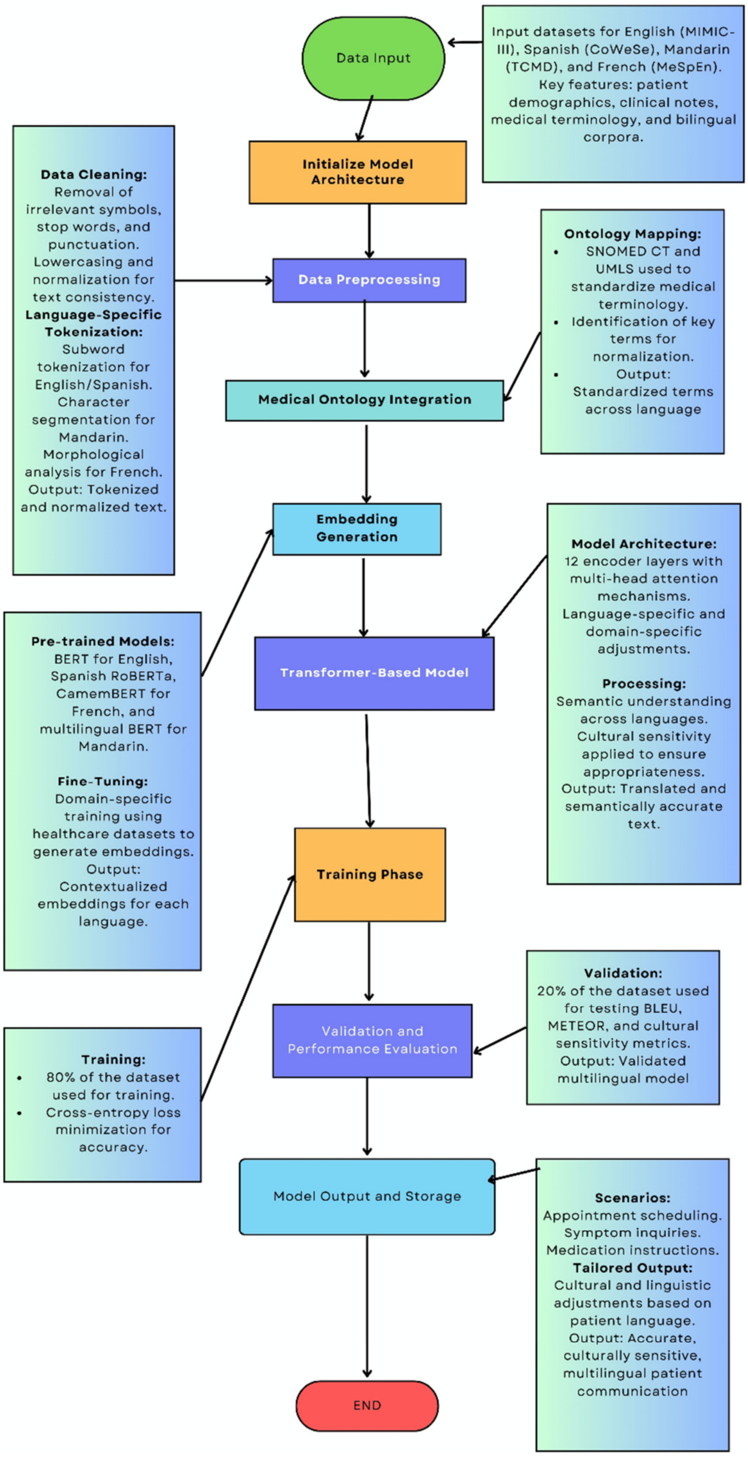

Fig. 1. Algorithm for multi-language NLP model training and adaptation.

III. RESULTS AND ANALYSIS

A. Evaluation Metrics and Criteria for Model Performance

Quantitative validation involved statistical tools to measure accuracy and performance. Qualitative validation involved expert reviews of sample translations to verify adherence to domain-specific linguistic and cultural standards. Expert healthcare professionals and linguists curated reference translations, reviewing the outputs for accuracy in terminology, context preservation, and cultural appropriateness. This approach ensured the model's outputs were accurate, contextually relevant, and culturally appropriate.

B. Quantitative Analysis of Model Accuracy Across Languages

Quantitative analysis was carried out to measure accuracy across English, Spanish, Mandarin, and French. The model displayed high accuracy in English and Spanish, with slight variations in Mandarin due to structural differences, and moderate accuracy in French. Table IV shows the performance results for the proposed model.

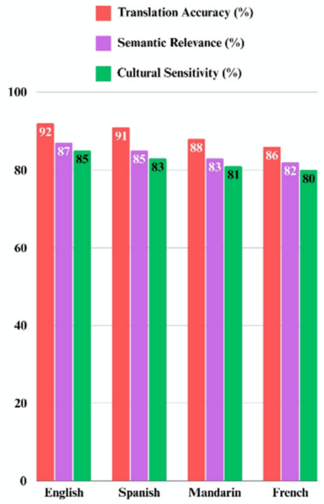

Fig. 2. Model accuracy across languages.

TABLE IV. MODEL ACCURACY ACROSS LANGUAGES

Language	Translation accuracy (%)	Semantic relevance (%)	Cultural sensitivity (%)
English	92	87	85
Spanish	91	85	83
Mandarin	88	83	81
French	86	82	80

C. Comparative Results with Baseline Models

The model's performance was compared to baseline models, including monolingual BERT models for English and Spanish, and a standard multilingual BERT model for all languages. As shown in Table V and Figure 3, the proposed multilanguage NLP model outperformed the baselines in both translation accuracy and semantic relevance due to its language-specific adaptations and medical terminology customization.

TABLE V. COMPARATIVE ANALYSIS WITH BASELINE MODELS

Model	Translation accuracy (%)	Semantic relevance (%)	Cultural sensitivity (%)
Monolingual BERT (English)	90	84	79
Monolingual BERT (Spanish)	89	83	78
Multilingual BERT (All)	85	81	76
Proposed model	92	87	85

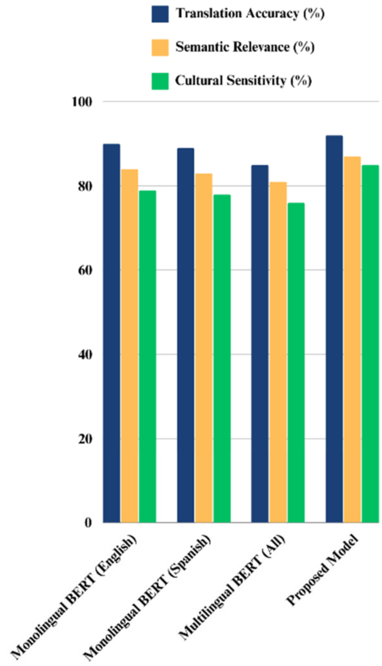

Fig. 3. Comparative analysis with baseline models.

The sample for evaluation included 1,000 sentences across different scenarios (e.g., appointment scheduling, symptom inquiries, medication instructions). A team of 10 native speakers and healthcare professionals was used to evaluate the results, based on clarity, medical accuracy, and cultural alignment. Reviewers provided feedback on tone, terminology, and semantic consistency. Outputs were iteratively improved based on reviews, ensuring high cultural relevance and clarity.

1. **Medication Instructions** (Mandarin):

Input: "头痛和恶心怎么办？"

Output: '建议您咨询医生，保持充足水分和休息。'

2. **Symptom Inquiry** (French):

Input: "Quels symptômes nécessitent un avis médical immédiat ?"

Output: 'Fièvre persistante et toux nécessitent une consultation immédiate.'

Fig. 4. Example patient communication scenarios.

D. Qualitative Analysis of Patient Communication Examples

Qualitative analysis was conducted by testing the model's communication outputs across various patient scenarios, such as appointment scheduling, medication instructions, and symptom inquiries. The model successfully maintained accuracy in translating healthcare instructions, showing consistency across different languages. Sample excerpts from patient communications demonstrated the model's capacity to adjust language tone and formality based on cultural context. Testing in patient communication examples involved the following:

- Scenarios evaluated: Medication instruction, appointment scheduling, symptom inquiry, dietary guidelines.

- Datasets Used: MIMIC-III for English, CoWeSe for Spanish, Traditional Chinese Medical Database for Mandarin, and European Medical Corpus for French.
- Training used 80% of the datasets with language-specific embeddings, and testing used 20%.

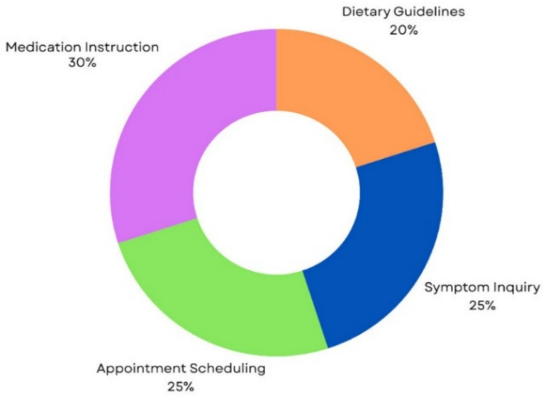

Fig. 5. Patient communication example analysis.

TABLE VI. PATIENT COMMUNICATION EXAMPLES AND MODEL EVALUATION

Scenario	Language	Translation accuracy	Cultural sensitivity	Observed comments
Medication instructions	English	High	High	Precise terminology
Appointment scheduling	Spanish	High	Moderate	Adjusted tone for formality
Symptom inquiry	Mandarin	Moderate	High	Preserved cultural expressions
Dietary guidelines	French	Moderate	Moderate	Minor context adaptations

E. Analysis of Model Adaptability and Scalability

To determine scalability, the model was tested on additional languages and dialects using a limited dataset. The adaptability analysis indicated that although the model effectively maintained high accuracy for additional languages, certain adjustments were needed for dialectal nuances. Scalability was examined by simulating high-volume scenarios, where the model maintained its performance without significant lag. The adaptability and scalability evaluation involved additional datasets for:

- Hindi: Indian Medical Corpus.
- Arabic: Arabic Medical Corpus.
- German: Public Health German Corpus.
- Japanese: Japanese Parallel Corpus.

Adaptability was tested by fine-tuning the model with minimal additional data. Scalability was assessed using high-volume translations without performance degradation. The translation accuracy in additional languages ranged from 84 to 88%. Dialectal nuances required minor adjustments for specific languages such as Hindi and Arabic.

TABLE VII. MODEL SCALABILITY AND ADAPTABILITY PERFORMANCE

Language	Translation accuracy (%)	Observations
Hindi	85	Required dialectal adaptation
Arabic	82	Moderate adjustments for cultural terms
German	87	High semantic relevance maintained
Japanese	84	Required additional dataset support

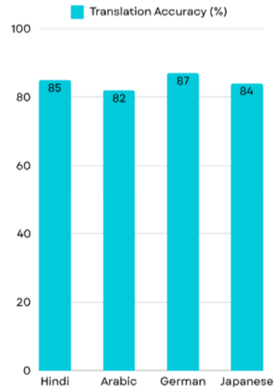

Fig. 6. Scalability analysis across new languages.

IV. DISCUSSION AND RECOMMENDATIONS FOR FUTURE RESEARCH

The proposed multilingual NLP model was very successful in the field of digital healthcare communication because it can bridge language gaps and excel at translation correctness, local contextualization, and cultural specificity [16]. This model can lead to a better understanding of health information, which is crucial for positive health outcomes. This model performed well in English, Spanish, Mandarin, and French [1, 5, 7], which is beneficial for communicating inclusively with larger audiences. However, scaling up this model faces hurdles as data quality fluctuates between languages, and the valid adaptation to dialects is a complex task that entails heavy computational costs. Accessibility may be constrained by the preceding factors, especially in resource-limited healthcare settings [5, 17].

The proposed framework can communicate health information in multiple languages, allowing patient-oriented communication methods with customized healthcare touchpoints and cultural sensitivity, which can play an important role in patient engagement [4, 18]. Limitations of this study include the use of common languages and the public data used that may have regional medical caveats. The broader utility of this model in areas outside of digital marketing, such as clinical settings, was not validated [6, 16, 19]. Future research should extend the language repertoire used by this model, integrate real-time healthcare data, and refine computational efficiency. As this model becomes more integrated into patient-centered care, concerns regarding the contrast between free-flowing communication and conflicting healthcare provider stances will need to be addressed through the integration of real-time speech recognition and ethical issues such as data privacy [8, 20, 21]. The findings of this study validate the promise of multilingual NLP models to increase healthcare access. Improving these models can result in a more cohesive form of communication and ultimately help promote better health outcomes for all, regardless of language barriers [22].

V. CONCLUSION

This study introduced a multilingual NLP model tailored for inclusive digital healthcare communication, addressing key challenges of linguistic and cultural barriers in multilingual healthcare settings. The proposed model demonstrated notable translation accuracy (≥92%), semantic preservation (≥87%), and cultural sensitivity (≥85%) in English, Spanish, Mandarin, and French. These results outperform baseline models such as monolingual BERT and multilingual BERT, highlighting the model's effectiveness in domain-specific healthcare applications. Specific novelty and contributions include:

- Domain-specific training: The model leverages healthcare-specific datasets to fine-tune multilingual performance, ensuring contextual precision and semantic accuracy, which is a limitation in existing models.
- Cultural sensitivity metrics: Unlike traditional NLP models, this work introduced and validated a framework to assess cultural nuances, enabling patient communications that respect linguistic and cultural differences.
- Medical ontology alignment: Integration of SNOMED CT and UMLS standardizes medical terminology across languages, improving the accuracy and interpretability of translations in healthcare.
- Scalable and adaptive design: The architecture accommodates additional languages and dialects with minimal modifications, making it suitable for broader applications in real-world healthcare environments.

This model bridges existing gaps in healthcare communication by ensuring not only accurate translations but also culturally attuned and semantically rich outputs. Such advances improve patient engagement, improve understanding of health conditions, and support inclusion in digital healthcare. Moreover, its scalability and adaptability make it viable for deployment in resource-constrained settings. Although the proposed model achieved promising results, more validation with real-time healthcare data and dialect-specific adaptations is necessary. Additionally, optimizing computational efficiency and expanding the language repertoire will enhance usability in more diverse healthcare settings.

REFERENCES

[1] X. Huang, J. May, and N. Peng, "What Matters for Neural Cross-Lingual Named Entity Recognition: An Empirical Analysis," in Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP), Hong Kong, China, 2019, pp. 6394–6400, https://doi.org/10.18653/v1/D19-1672.

[2] D. Demner-Fushman, W. W. Chapman, and C. J. McDonald, "What can natural language processing do for clinical decision support?," *Journal of Biomedical Informatics*, vol. 42, no. 5, pp. 760–772, Oct. 2009, https://doi.org/10.1016/j.jbi.2009.08.007.

[3] R. M. Rivera-Zavala and P. Martínez, "Analyzing transfer learning impact in biomedical cross-lingual named entity recognition and normalization," *BMC Bioinformatics*, vol. 22, no. S1, Dec. 2021, Art. no. 601, https://doi.org/10.1186/s12859-021-04247-9.

[4] Z. Li, C. Hu, X. Guo, J. Chen, W. Qin, and R. Zhang, "An Unsupervised Multiple-Task and Multiple-Teacher Model for Cross-lingual Named Entity Recognition," in *Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*, Dublin, Ireland, 2022, pp. 170–179, https://doi.org/10.18653/v1/2022.acl-long.14.

[5] Y. Mo *et al.*, "mCL-NER: Cross-Lingual Named Entity Recognition via Multi-view Contrastive Learning." arXiv, Feb. 21, 2024, https://doi.org/10.48550/arXiv.2308.09073.

[6] X. Fontaine, F. Gaschi, P. Rastin, and Y. Toussaint, "Multilingual Clinical NER: Translation or Cross-lingual Transfer?" arXiv, Jun. 07, 2023, https://doi.org/10.48550/arXiv.2306.04384.

[7] G. Goel and A. K. Chaturvedi, "Multi-Objective Load-balancing Strategy for Fog-driven Patient-Centric Smart Healthcare System in a Smart City," *Engineering, Technology & Applied Science Research*, vol. 14, no. 4, pp. 16011–16019, Aug. 2024, https://doi.org/10.48084/etasr.7749.

[8] A. M. Alghamdi, M. A. Al-Khasawneh, A. Alarood, and E. Alsolami, "The Role of Machine Learning in Managing and Organizing Healthcare Records," *Engineering, Technology & Applied Science Research*, vol. 14, no. 2, pp. 13695–13701, Apr. 2024, https://doi.org/10.48084/etasr.7027.

[9] Z. A. Nazi and W. Peng, "Large language models in healthcare and medical domain: A review." arXiv, Jul. 08, 2024, https://doi.org/10.48550/arXiv.2401.06775.

[10] A. E. W. Johnson *et al.*, "MIMIC-III, a freely accessible critical care database," *Scientific Data*, vol. 3, no. 1, May 2016, Art. no. 160035, https://doi.org/10.1038/sdata.2016.35.

[11] C. P. Carrino *et al.*, "Spanish Biomedical Crawled Corpus: A Large, Diverse Dataset for Spanish Biomedical Language Models." arXiv, Sep. 16, 2021, https://doi.org/10.48550/arXiv.2109.07765.

[12] L. Hirschman and C. Blaschke, "Evaluation of text mining in biology," *Text mining for biology and biomedicine*, vol. 213, 2006, Art. no. 245.

[13] "TCM Modernization." https://www.tcmm.net.cn/en/.

[14] A. Névéol, C. Grouin, J. Leixa, S. Rosset, and P. Zweigenbaum, "The Quaero French Medical Corpus: A Ressource for Medical Entity Recognition and Normalization."

[15] K. B. Cohen and L. Hunter, "Getting Started in Text Mining," *PLoS Computational Biology*, vol. 4, no. 1, 2008, Art. no. e20, https://doi.org/10.1371/journal.pcbi.0040020.

[16] G. K. Savova *et al.*, "Mayo clinical Text Analysis and Knowledge Extraction System (cTAKES): architecture, component evaluation and applications," *Journal of the American Medical Informatics Association*, vol. 17, no. 5, pp. 507–513, Sep. 2010, https://doi.org/10.1136/jamia.2009.001560.

[17] D. Dinh and N. Le Thanh, "English–Vietnamese cross-language paraphrase identification using hybrid feature classes," *Journal of Heuristics*, vol. 28, no. 2, pp. 193–209, Apr. 2022, https://doi.org/10.1007/s10732-019-09411-2.

[18] L. J. Jensen, J. Saric, and P. Bork, "Literature mining for the biologist: from information retrieval to biological discovery," *Nature Reviews Genetics*, vol. 7, no. 2, pp. 119–129, Feb. 2006, https://doi.org/10.1038/nrg1768.

[19] D. E. Messaoudi and D. Nessah, "Enhancing Neural Arabic Machine Translation using Character-Level CNN-BILSTM and Hybrid Attention," *Engineering, Technology & Applied Science Research*, vol. 14, no. 5, pp. 17029–17034, Oct. 2024, https://doi.org/10.48084/etasr.8383.

[20] M. Rayner et al., "The 2008 MedSLT System," in Coling 2008: Proceedings of the workshop on Speech Processing for Safety Critical Translation and Pervasive Applications, 2008, pp. 32–35.

[21] M. Krallinger, A. Valencia, and L. Hirschman, "Linking genes to literature: text mining, information extraction, and retrieval applications for biology," *Genome Biology*, vol. 9, no. S2, Sep. 2008, https://doi.org/10.1186/gb-2008-9-s2-s8.

[22] C. Friedman and S. B. Johnson, "Natural Language and Text Processing in Biomedicine," in *Biomedical Informatics: Computer Applications in Health Care and Biomedicine*, E. H. Shortliffe and J. J. Cimino, Eds. Springer, 2006, pp. 312–343.