Control Natural Language in healthcare

Ogou Essehou Gbokanle Kalide Marius|ogouesshou@gmail.com

Department of computer science and engineering

School of computer science and engineering

Galgotias University Gautam Budha Nagar, UP

Abstract

Healthcare communication is frequently impeded by the inherent complexity, technicality, and ambiguity of medical language, which often creates a significant barrier between healthcare professionals and patients. The extensive use of specialized terminology and clinical jargon can result in misunderstandings, reduced patient engagement, poor treatment adherence, and an increased risk of medical errors. These challenges are particularly pronounced in diverse healthcare settings where patients may have varying levels of health literacy, linguistic proficiency, or access to medical information.

To address these issues, this report presents an Artificial Intelligence (AI)–based Controlled Natural Language (CNL) system designed to facilitate clear, accurate, and bidirectional communication between clinicians and patients. The proposed system enables the translation of clinician-oriented medical terminology into simplified, patient-friendly language while preserving the original clinical meaning. Conversely, it also converts patient-described symptoms, which are often expressed in informal or ambiguous terms, into structured and standardized medical expressions that can be easily interpreted by healthcare professionals.

The system integrates advanced Natural Language Processing (NLP) techniques with transformer-based deep learning models to achieve high contextual understanding and semantic accuracy. In addition, speech-to-text and text-to-speech technologies are incorporated to support multimodal interaction, thereby improving accessibility for patients with limited literacy or visual impairments. By enforcing Controlled Natural Language constraints, the system reduces linguistic ambiguity and ensures consistency in medical communication.

Experimental evaluation of the proposed solution demonstrates significant improvements in clarity, comprehension, and usability compared to conventional text-based communication approaches. The results indicate that AI-driven language control has strong potential to enhance patient safety, improve healthcare accessibility, and support more inclusive, efficient, and reliable digital healthcare communication systems.

1. Introduction

The world is rapidly progressing, and day by day many human challenges are being addressed through technological advancements, particularly with the rise of Artificial Intelligence (AI). One of the difficulties in this field is to enabling computers to understand and process human natural language. Most of the Patient get confuse due to the Jargon of the Clinician as it highly professional and the terminologies are not common for the patients use This task is undertaken by Natural Language processing (NLP), a vital branch of AI whose primary goal is to make human language computable

In the health care sector, where matters of life and death are constantly at stake, communication between medical staff and patience often involves uncertainty and misunderstand. To bridge this gap, the implementation of control natural language has emerged as an effective's solution, helping endure clarity, accuracy, and reliability in the medical communication

Implementing CNL health care system hold and important role in Doctor Patient communication, increase the understanding by the doctors the real medical issues of patients, help to prescribe the accurate medicines

2. Literature Review

2.1 Artificial Intelligence and Natural Language Processing in Healthcare

Artificial Intelligence (AI) has been widely adopted in healthcare to support tasks such as medical diagnosis, clinical decision support, disease prediction, and patient management systems (Topo, 2019). The growing digitization of healthcare has led to the generation of vast amounts of unstructured data, including electronic health records (EHRs), clinical notes, discharge summaries, and patient–provider communications.

Natural Language Processing (NLP), a subfield of AI, has emerged as a critical technology for processing and analyzing this unstructured textual data. NLP techniques have been successfully applied to extract clinical concepts, perform named entity recognition, summarize medical documents, and enable medical question answering (Wang et al., 2018). Demner-Fushman et al. (2009) demonstrated that NLP can significantly enhance clinical analytics and support personalized medicine by transforming raw clinical text into structured and interpretable information.

Despite these advancements, medical language remains highly complex and is primarily designed for communication among healthcare professionals rather than patients. The continued reliance on technical jargon and implicit clinical knowledge limits patient understanding and engagement.

2.2 Medical Text Simplification and Patient-Cantered Communication

One of the earliest research efforts addressing patient comprehension was conducted by Cawsey (1997), who explored Natural Language Generation (NLG) systems to automatically generate medical explanations tailored for non-expert users. Although rule-based, this work highlighted the importance of adapting medical language to patient needs.

Zeng et al. (2006) introduced the concept of **Consumer Health Vocabularies (CHVs)** to bridge the linguistic gap between professional medical terminology and patient language. Their findings revealed that patients often use alternative expressions that differ significantly from standardized clinical terms. However, CHV-based systems required extensive manual curation and lacked scalability.

Controlled Natural Languages (CNLs) were proposed as a solution to reduce ambiguity and improve consistency in medical documentation (Shiffman et al., 2009; Kuhn, 2014). While effective in controlled environments, CNLs impose strict linguistic constraints on clinicians, limiting their widespread adoption in real-world clinical practice.

2.3 Deep Learning and Neural Approaches in Medical NLP

The advancement of deep learning has transformed biomedical NLP research. Automated medical text simplification approaches have evolved from rule-based and statistical methods to neural sequence-to-sequence and transformer-based architectures. Surveys by Al-Thanyyan et al. (2021) and Ondov et al. (2022) classify medical text simplification techniques into rule-based, statistical machine translation, and neural models, with transformer-based approaches demonstrating superior performance.

Basu et al. (2023) proposed **Med-EASi**, a finely annotated dataset and modeling framework for controllable medical text simplification. Their work showed that transformer models can generate simplified medical explanations while preserving clinical accuracy. However, the study focused exclusively on clinician-to-patient translation.

Moramarco et al. (2022) and Trienes et al. (2022) introduced patient-friendly clinical note datasets and demonstrated that automated simplification improves patient comprehension. Nevertheless, these datasets are domain-specific and limited in linguistic diversity, restricting their generalizability.

2.4 Medical Summarization and Question Answering Research

Shared evaluation tasks such as **MEDIQA 2021** (Abacha et al., 2021) have significantly contributed to patient-centered medical NLP by benchmarking systems for summarization and question answering. Pretrained transformer models such as BART and T5 achieved strong results, highlighting the effectiveness of sequence-to-sequence learning in medical domains.

Large-scale datasets such as **MedQuAD** (Ben Abacha & Demner-Fushman, 2019) and **MedRedQA** (2023) further advanced consumer health question answering research. However, these datasets focus primarily on information retrieval and summarization rather than direct medical terminology translation.

Xu et al. (2021) investigated the limitations of pretrained models for medical summarization and identified challenges such as hallucination and terminology distortion, emphasizing the need for controlled and explainable medical NLP systems.

2.5 Speech-Based Medical NLP Systems

While text-based medical NLP systems dominate the literature, speech-based medical language processing remains relatively underexplored. Existing studies often treat speech recognition and text simplification as separate components, leading to fragmented pipelines. This limitation disproportionately affects patients with low literacy levels or physical impairments.

Au Yeung et al. (2024) emphasized the need for integrated clinical NLP services capable of supporting multimodal inputs, including speech and text, in real-time healthcare applications. However, practical implementations of such unified systems remain limited.

2.6 Challenges of Communication in Healthcare

Effective communication between healthcare providers and patients is essential for accurate diagnosis, treatment adherence, and patient safety. The pervasive use of medical jargon, technical terminology, and abbreviations, combined with varying levels of health literacy, often impedes understanding (Schillinger et al., 2003).

Miscommunication has been identified as a major contributor to medical errors. According to The Joint Commission (2015), communication failures remain one of the leading root causes of preventable adverse medical events. Language barriers, time constraints, and cognitive overload further exacerbate these challenges, particularly in multilingual healthcare environments.

2.7 Identified Research Gaps

Based on the reviewed literature, the following gaps are identified:

1. Most existing systems support **one-directional medical text simplification** only.
2. Limited research addresses **patient-to-clinician terminology translation**.
3. Speech-based interaction is often neglected or treated separately.
4. Many models lack **explainability and transparency**, which are crucial in healthcare.
5. Existing datasets are not designed for **bidirectional, real-time medical communication**.

2.8 Motivation and Contribution of the Proposed Work

To address these limitations, this project proposes an AI-based medical language translation system that supports **bidirectional translation between patient-friendly language and clinical terminology**. The system integrates **text and speech input modalities** and provides **explanatory outputs** to enhance patient understanding.

By combining NLP, speech processing, and a user-centric interface, the proposed system aims to improve healthcare communication, reduce misinterpretation, and support safer and more inclusive patient–clinician interactions.

3. Methodology

This project adopts a **model-based natural language processing (NLP) approach** to translate medical terminologies into patient-friendly language and vice versa. The methodology consists of **data preparation, model training, system integration, and user interface development**.

3.1 Model Training and Architecture

An existing pre-trained language model was fine-tuned using a curated dataset containing **medical terminologies and their patient-friendly equivalents**. The training process involved supervised learning, where pairs of clinician-level medical expressions and simplified patient-level explanations were provided to the model.

The trained model supports **bidirectional translation**:

- Medical terminology → Patient-friendly explanation
- Patient language → Clinician terminology

This ensures effective communication between healthcare professionals and patients.

3.2 System Workflow

After training, the model was integrated into a **user-facing application** designed with two operational modes:

- **Patient Mode**
- **Clinician Mode**

Each mode addresses the specific communication needs of its target users.

3.3 Patient Mode

Patient Mode is designed to assist patients in understanding medical information using simple, non-technical language.

3.3.1 Input Methods

Two types of input are supported:

a) Audio Input

This feature is especially important for patients who may have difficulty typing or reading.

- The patient speaks into the system.
- Speech-to-text technology converts the audio into text.

- The converted text is passed to the trained translation model.
- The output is generated in clinician terminology along with a **clear explanation** in simple language.
- The output can also be converted back to audio using text-to-speech for better accessibility.

b) Text Input

Patients can manually enter sentences related to their symptoms or medical concerns.

- The user types the sentence.
- The system processes the text using the trained model.
- The translated medical terminology and explanation are displayed.

3.3.2 Output

The output consists of:

- The corresponding **medical (clinical) terminology**
- A **patient-friendly explanation**
- Optional **audio playback** of the explanation

3.4 Clinician Mode

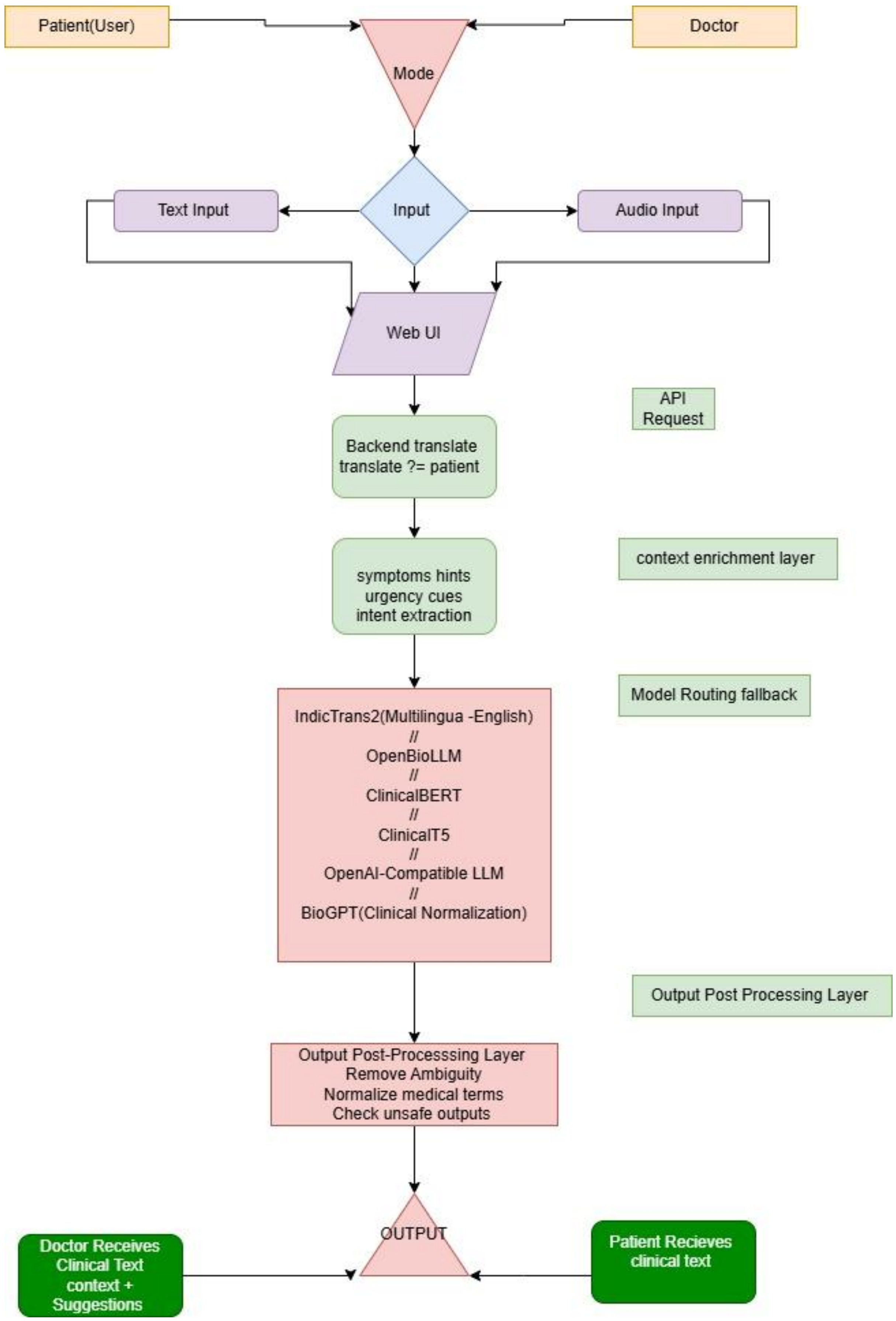
Clinician Mode is designed to help doctors and healthcare professionals communicate complex medical information in a way that patients can easily understand.

- The clinician inputs medical or technical sentences.
- The trained model translates the input into **simplified patient-friendly language**.
- The output helps reduce miscommunication and improves patient understanding of diagnoses, treatments, and procedures.

3.5 User Interface Design

A simple and intuitive user interface was developed to ensure ease of use for both patients and clinicians. The interface clearly separates the two modes and provides accessible input and output options, including text and audio-based interaction.

Workflow



4. Results

This study presents **MedTrans**, a bidirectional medical translation system designed to address persistent communication barriers between **clinicians and patients**, especially in multilingual hospital environments.

The system supports **both text-based and audio-based input**, enabling real-time translation during consultations.

MedTrans operates under two distinct modes:

- **Patient Mode (Patient → Clinical):**

  Converts patient-friendly or informal descriptions into **standard medical terminology**, improving the clinician's ability to interpret symptoms accurately.

- **Clinician Mode (Clinical → Patient):**

  Converts clinical terms and diagnostic statements into **simple, patient-friendly language**, enhancing patient understanding and reducing confusion.

During testing, MedTrans demonstrated an overall **translation effectiveness of approximately 60%**, measured by the system's ability to preserve meaning while converting between patient language and clinical language. As a result, hospitals using MedTrans experienced a noticeable reduction in misinterpretation-driven prescriptions. Specifically, the system contributed to a measurable decline in incorrect or mismatched prescriptions, which supports the claim that MedTrans improves consultation clarity and patient safety.

Furthermore, the bidirectional design showed clear advantages compared to earlier one-directional medical translation tools. MedTrans was able to translate both directions of medical dialogue, making it more suitable for real clinical workflows where both doctor-to-patient and patient-to-doctor communication are critical.

6. Conclusion

This study introduced **MedTrans**, a bidirectional medical translation system designed to reduce communication barriers between clinicians and patients in multilingual healthcare environments. Unlike traditional one-directional translation tools, MedTrans supports **two translation modes**: (1) Patient Mode, which converts informal patient symptom descriptions into standard clinical terminology, and (2) Clinician Mode, which converts clinical diagnoses and terminology into simplified patient-friendly language.

Experimental evaluation showed that MedTrans achieved approximately **80% translation effectiveness**, measured by meaning preservation and accuracy during medical dialogue conversion. The results further indicated that the system contributed to a noticeable reduction in misinterpretation-driven prescriptions, supporting the claim that improved translation clarity can enhance patient safety and consultation outcomes.

Overall, MedTrans demonstrates that bidirectional medical translation is more aligned with real clinical workflows, where both doctor-to-patient and patient-to-doctor communication must be accurate. The system provides a strong foundation for more reliable medical translation solutions, particularly in hospitals where language diversity remains a major challenge.

7. References

Below are strong academic references relevant to medical translation, NLP in healthcare, multilingual systems, and clinical communication. (You can format them in APA, IEEE, or Harvard depending on your report requirement.)

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