

Natural Language Processing in Healthcare: A Bird's Eye View

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Abstract

The healthcare industry is experiencing an unprecedented era of transformation, driven by the proliferation of Electronic Health Records (EHRs) and the emergence of vast amounts of natural language data from sources like social media. This dynamic landscape presents novel opportunities for companies, healthcare practitioners, and researchers, underpinned by the transformative potential of Natural Language Processing (NLP) technologies. This paper offers a brief overview of the rationale for studying NLP in healthcare, highlighting its foundational importance. It explores the current trends and invaluable resources available in the field, while also delving into the multifaceted challenges that must be addressed to harness the full potential of NLP in healthcare. By consolidating essential insights and bridging the gap between opportunities and challenges, this manuscript serves as a valuable resource for both established researchers and newcomers seeking to navigate the complex terrain of NLP in healthcare, ultimately contributing to the advancement of this critical domain.

Keywords

Natural Language Processing, Healthcare, Review, Electronic Health Records

1. Introduction

When we mention Artificial Intelligence (AI) in healthcare, we often imagine systems adept at interpreting sensor data — such as time series from physiological measurements and medical images — to provide invaluable diagnostic support to healthcare professionals and patients alike. However, a substantial portion of patient information moves through the healthcare ecosystem in the form of natural language narratives [2]. These textual data hold immense potential (and need) for automated processing and analysis.


The past few decades have witnessed a profound digital transformation across industries, including healthcare. This transformation has unleashed a torrent of data from diverse sources alongside new opportunities and challenges. The opportunities offered by Natural Language Processing (NLP) in healthcare are vast and intricate, rendering a comprehensive review im-


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practical. For newcomers venturing into this field, navigating this complex landscape can be overwhelming.

In recent years, several researchers have undertaken the task of dissecting this field from various angles. Some have focused on the learning techniques employed in the literature, such as machine and deep learning [3, 4]. Others have focused on specific data sources, either electronic health records from healthcare institutions or unstructured data from social media platforms [5, 6, 7]. Among those works, Gao et al. [8] have compiled a valuable resource by cataloging publicly available datasets in clinical NLP, which researchers are exploiting to overcome privacy concerns (see Section 4). Nonetheless, most of these investigations have revolved around specialized subdomains within healthcare and clinical practices, such as mental health [9], orthopedics [10], and dentistry [11].

Thus, this paper aims to provide a concise overview of the panorama of NLP in healthcare, offering condensed insights into data sources, tools, current trends, and persistent challenges, providing a guiding beacon, especially for NLP researchers and practitioners embarking on the healthcare field.

2. Data sources

Electronic Health Records (EHRs) The healthcare industry is in the midst of a rapid digital transformation, marked by the widespread adoption of Electronic Health Records (EHRs), also known as Electronic Medical Records (EMRs), in hospitals and clinics worldwide [12, 13]. These clinical documents often contain approximately 80% of unstructured data [14], primarily as free text. In clinical practice, healthcare professionals exchange patient information as narrative notes and reports [2].

Besides offering a more comprehensive description of a patient's health status compared to quantitative data alone, these natural language reports can be time-consuming to understand and redact. Not surprisingly, the development of NLP in the healthcare sector has paralleled the increasing adoption of EHRs. NLP tools have emerged as essential solutions for efficiently managing unstructured data within these records. Automatically analyzing patients' records not only facilitates access to a wealth of information but also serves the needs of physicians, healthcare companies, patients, and researchers.

The World Wide Web (WWW) In addition to EHRs, the proliferation of the World Wide Web (WWW) has opened up new opportunities for the NLP community to harness data from sources like forums and social media to enhance healthcare services [5]. Given the vast volume of text-based information exchanged daily on the WWW, this digital landscape presents an unprecedented opportunity for NLP researchers and practitioners. It serves as an invaluable source of textual data for training NLP systems, often through web scraping technologies [15]. Beyond general-purpose social media platforms, the WWW has spawned specialized online health communities such as PatientsLikeMe¹ and DailyStrength². These platforms bring together users with similar health-related interests and concerns. Other platforms on the Internet consist

¹<https://www.patientslikeme.com/>

²<https://www.dailystrength.org/>

of websites for spreading medical information. NLP researchers are already making use of resources like Wikipedia and SimpleWikipedia³, and the MSD Manuals⁴ [16].

3. Tasks

Within the vast panorama of NLP applied to healthcare, various tasks exist, each offering benefits to multiple stakeholders. Although the division proposed here is not an absolute categorization (i.e., some of the solutions may benefit more stakeholders), it serves as a handy framework for understanding the diverse applications of NLP in this domain.

Tasks for physicians NLP tasks designed for physicians predominantly revolve around the generation/extraction of critical information from EHRs. These tasks serve as tools for lightening the workload of healthcare professionals and enhancing decision support for physicians [6]. For instance, the development of Natural Language Generation (NLG) systems proves invaluable in creating clinically precise structured reports from various clinical documents or condensing the extensive notes generated daily throughout the care process [17]. Conversely, Natural Language Understanding (NLU) systems function as Information Extraction tools, directly harvesting pertinent data from these reports, encompassing diagnoses, medication records, treatment plans, and other essential entities. Through these functionalities, NLP systems show the potential to empower clinicians with evidence-based recommendations and timely alerts, elevating the caliber of medical decision-making. Simultaneously, they alleviate the burdens associated with manual data entry, enhancing efficiency and accuracy in healthcare practice.

Tasks for institutions Automated analysis of text data within EHRs holds tremendous significance in enhancing the management of healthcare services provided by organizations. For instance, healthcare institutions can harness NLP to predict the risk of patients' readmissions. This predictive capability facilitates the implementation of targeted interventions, optimizes resource allocation, reduces hospital readmission rates, and ultimately lowers costs [18].

Another valuable application of text analysis in EHRs involves streamlining administrative tasks for healthcare facilities. It is achieved by automating the coding activities involved in billing processes. Diagnoses and procedures are usually encoded using standardized nomenclatures such as the International Classification of Diseases (ICD), overseen by the World Health Organization (WHO). These codes simplify health data comparison across populations and support epidemiological analyses. Currently, the responsibility for this classification process often falls on trained or even untrained personnel within healthcare institutions. Given the task complexity and time-intensive nature, it poses challenges even for professionally trained staff and is prone to errors. These errors can result in financial losses and potential legal consequences. Consequently, there is a growing interest in developing automatic systems for ICD coding, as evidenced by various research efforts [19] focused on clinical note extraction, such as discharge summaries.

³https://en.wikipedia.org/wiki/Main_Page, https://simple.wikipedia.org/wiki/Main_Page

⁴<https://www.msdmanuals.com/>

Beyond EHRs, the World Wide Web (WWW) is a crucial resource for healthcare institutions. NLP-driven surveillance systems can actively monitor digital sources, enabling the early detection of disease outbreaks, emerging trends, and even signs of suicidal intentions [20, 21], allowing timely and proactive responses.

Moreover, just as consumers seek product or service reviews before making decisions, patients actively seek and share health-related experiences online [22, 23]. Healthcare companies can derive significant benefits from automating the analysis of patients' opinions to identify strengths and weaknesses in their services and treatments. Automated tools offer the advantage of processing a vast number of reviews, eliminating the need for traditional structured surveys and questionnaires that limit patient expressiveness and are costly and time-consuming to design and analyze. This type of analysis is commonly known as sentiment analysis or opinion mining, a task that has garnered extensive attention in various domains within the NLP community, yet remains relatively underexplored in healthcare [24].

Tasks for patients The World Wide Web (WWW) empowers patients to access a wealth of information, one of the Internet's foremost virtues being its democratic provision of easy access to vast knowledge resources. However, the abundance of medical information available online can pose challenges for patients without medical backgrounds, who may misinterpret these resources [25], potentially leading to harmful consequences. In this context, NLP is emerging as a valuable tool for simplifying health-related texts, bridging the expertise gap for patients [16, 26]. However, the Internet, particularly on social media and similar platforms, can be disseminated with medical misinformation. Consequently, several researchers have recently dedicated their efforts to detecting health-related fake news and combatting what has been termed the *infodemic* [27, 28].

Another popular application benefiting patients is chatbots, digital agents designed for interactive conversations with users. These chatbots offer a friendly and engaging means of educating patients to enhance adherence to care treatments and provide real-time support for their decision-making skills. Notably, studies have shown that patient education becomes more effective with increasing interactions with care providers number [29]. In this context, chatbots hold significant promise for helping patients cultivate healthier habits at scale, ultimately reducing hospital admissions, healthcare costs, and time commitments. Within this framework, NLP solutions have already begun to play a pivotal role as *healthbots*: Parmar et al. [30] conducted a review of healthbots available on the major mobile app stores. However, their findings revealed that most healthbots rely on rule-based approaches and finite-state dialogue management, leaving space for the latest advancements in NLP for application in healthcare.

Tasks for biomedical researchers NLP represents an unprecedented opportunity for biomedical researchers. Apart from employing NLP to extract and summarize information from vast biomedical literature databases, researchers can exploit its techniques to ease the recruitment of patients for studies by identifying people meeting the study criteria from the clinical notes [31, 32], perhaps with appropriate adjustments to handle variations in clinical documentation between different institutions [33]. This expedient leads to building larger cohorts with fewer efforts, which is extremely useful for researchers in the biomedical field.

Furthermore, NLP can be employed to annotate patients' health status from their reports, providing *silver labels* to associate with other kinds of data, like images, and then train the principal AI system, which is often data-hungry, in a supervised way [10].

4. Challenges

The integration of NLP in healthcare has encountered and continues to face unique challenges. The main concern is the imperative to safeguard patient privacy, given that narrative reports within healthcare are filled with sensitive information governed by stringent legislation, such as the U.S. Health Insurance Portability and Accountability Act (HIPAA) and the European Union's General Data Protection Regulation (GDPR). The implications of these regulations are profound, demanding the implementation of appropriate measures to protect individuals' privacy. However, the costs and reliability challenges associated with de-identifying health reports present a prominent hurdle for the NLP community in healthcare. These issues constrain access to shared data, inhibiting collaboration and reproducibility among researchers' teams [34]. Not surprisingly, the first shared task for clinical NLP in 2006, the *Integrating Biology and the Bedside* (i2b2), was centered on the automated removal of Private Health Information (PHI) from medical discharge records [35].

To handle this issue, many researchers have focused their efforts on publicly accessible clinical note databases. For example, databases like the Medical Information Mart for Intensive Care (MIMIC)⁵ have enabled researchers to work with extensive datasets, surmounting regulatory obstacles. Also, the recent DR.BENCH [36] has emerged as a new benchmark for model development/evaluation for diagnostic reasoning based on EHRs.

Furthermore, medical and clinical languages present their own complexities [37], encompassing numerous clinical, biological, and medical subdomains, each characterized by its own lexicon, acronyms, abbreviations, ambiguous terms, entities, and variations. To address this challenge, some experts have developed resources such as lexicons, ontologies, and tools tailored for medical and clinical languages. Resources like the Unified Medical Language System (UMLS)⁶, along with auxiliary tools such as MetaMap⁷, cTakes⁸ and CLAMP⁹, as well as adapted advanced models and representations [38] serve as valuable assets for NLP practitioners. However, applying these tools to analyze diverse sources like social media, which may exhibit significant language variations, can potentially undermine the effectiveness of such tools [39].

In light of the scarcity of data and the intricacies of a domain-specific language, the issue of multilingualism assumes significance. A majority of the research efforts are oriented towards English, likely due to the lack of available resources in other languages [40].

In addition, the imperative of *explainability* emerges as a critical factor of contemporary research, particularly within healthcare. The lack of interpretability undermines the acceptance and trust of AI and NLP systems in this sensitive domain among both patients and healthcare practitioners [41].

⁵<https://mimic.mit.edu/>

⁶<https://www.nlm.nih.gov/research/umls/index.html>

⁷<https://lhncbc.nlm.nih.gov/ii/tools/MetaMap.html>

⁸<https://ctakes.apache.org/>

⁹<http://clamp.uth.edu/index.php>

5. Conclusions

In conclusion, this short paper offers a bird's eye view into the multifaceted panorama of NLP in healthcare, showcasing its significant potential to benefit multiple stakeholders. It encompasses patients seeking personalized health information, healthcare institutions working to streamline their operations, physicians needing clinical decision support, and researchers delving into the complexities of diseases, catalyzing a transformative change in the healthcare landscape.

Nonetheless, NLP in healthcare extends beyond pure academic research; it is a thriving field with real-world applications that can significantly enhance patient care. Moreover, as NLP techniques continue to advance and adapt, an exciting frontier full of unexploited opportunities for researchers and practitioners unfolds.

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