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Chapter 5

Natural language processing in healthcare: Unlocking insights from clinical data

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Abstract:

Natural Language Processing (NLP) is transforming healthcare by extracting valuable insights from clinical data. By analyzing unstructured text in medical records, NLP enables efficient information retrieval, enhances decision-making, and supports improved patient care by identifying patterns, trends, and key clinical data for better treatment outcomes.

Keywords

Clinical Data, Decision-Making, Healthcare, Insights, Natural Language Processing, Patient Care

5.1. Introduction

Unstructured data in the healthcare sector accounts for a majority of data generated today. Containing patient interactions with the healthcare system and their health status, this data is captured in clinical notes and narratives within the electronic health record system. This unstructured data holds a wealth of information and insights, but harnessing it presents several challenges. Traditional methods focus mainly on structured data collected for billing or discrete standardized clinical codes for conditions and procedures. These methods do not provide detailed information on the care delivered and often lack patient context. As healthcare leaders continue to seek improved cost, quality, and patient satisfaction metrics, insights from the unstructured data within EHRs will become a strategic priority. Unlocking the real-world evidence to support decision-making, quality improvement, and research will, by necessity, require increased use of advanced machine learning, particularly natural language processing, and NLP-enabled technologies. NLP is at the inflection point in demonstrating transformational value in near-enough real-world settings. Regardless of the complexity and nuance within clinical narratives, the effective use of NLP can facilitate higher-quality patient care, improve the efficiency of operations, and quicken research advancements. The foundation of a chance to uncover insights and patterns from large data sets and pointed questions lies within the capability to analyze clinical notes, cases, narratives, transcripts, and charts accurately, promptly, and securely.

This document endeavors to elucidate the business case for NLP technologies, best use cases, and how some tools, analytics, and solutions are being utilized with real-world examples (Danda, 2024). Also, this document establishes the need to address incorrectly presumed paradigms of today's healthcare and life sciences organizations. As such, it seeks to set the stage for NLP innovation in a healthcare business environment, with 2022 being seen as the year to spearhead NLP possibilities. Part 2 of this two-part document is a practical guide for healthcare and life sciences leaders and organizations to plan or align their company's or individual next steps about NLP. It provides a roadmap to adopt NLP within their companies and to rethink or redirect their technology investment strategies.

5.1.1. Background and Significance

Hospitals and clinicians are responsible for generating more patient data than ever before. An estimated 80% of this patient care data takes unstructured forms such as dictated clinical notes, report transcriptions, discharge summaries, and radiology and pathology reports. The volume of unstructured data is poised to contribute the lion's share of any such increase. These facts taken together make it plausible to state that some 40 petabytes of clinical notes are being generated per year in the United States. This estimate dwarfs the size of all unstructured data sets this community has ever worked with. Encouragingly, the contours of this challenge are congruent with the emergence in recent years of data-mining techniques and tools that have the potential to be repurposed to the challenges of mining clinical notes. These tools, predicated on natural language processing and machine learning, permit a level of sophistication and insight into unstructured text commensurate with the evolving complexity of healthcare.

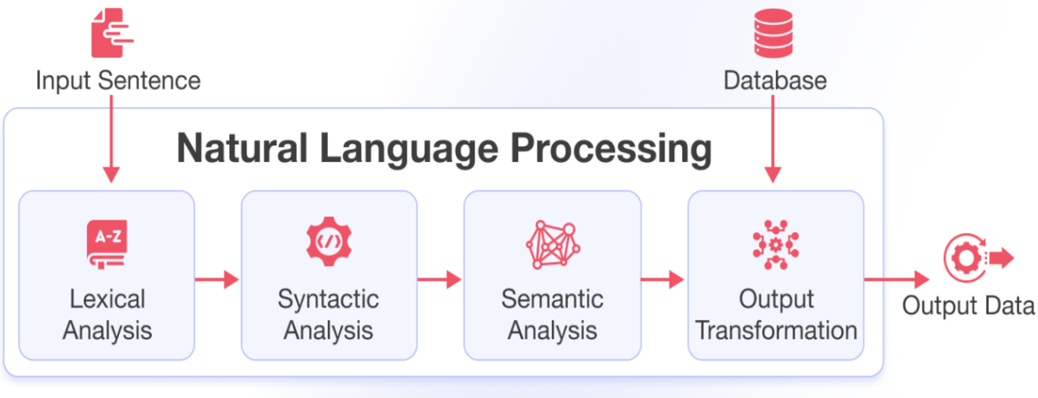

Fig 5 . 1 : The Revolutionizing Effects of NLP in the Healthcare Industry

For patients and caregivers, the benefits in patient care and outcome measurement of analyzing those 40 petabytes are not negligible. Yet we know from cleaning clinical corpora that a volume higher than even two or three petabytes will remain largely untapped and unavailable for secondary uses unless NLP methods are applied. Once cleaned and analyzed, those volumes of clinical narratives may yet yield the results they were collected to provide: personalized risk profiling and decision support, new leads for the methodology of personalized medicine, and new outcomes and endophenotypes that are actionable and lead to a better understanding of the individual's health. Two of the top ten American pharmaceutical companies each used information extraction from clinical narratives to build knowledge that affects patient health and safety. There are grave concerns about the growing gap in the use of patient data in patient care and the use of de-identified patient data for learning that benefits society at large. NLP represents one means to span that gap. These statements offer a contemporary rationale for NLP research.

5.1.2. Purpose of the Research

The paper seeks to examine the field of natural language processing (NLP) in the context of healthcare. In particular, the paper will focus on the use of NLP for developing insights for healthcare practitioners from clinical data. The literature paints a picture of a divide between the theoretical capabilities of NLP and its practical implementations. Similarly, the practical implementations of NLP in healthcare are associated with both great benefits and great obstacles (Syed, 2023). Here, the intention is to focus on how NLP is being used, the obstacles it faces, and its performance in use.

An important question to pose about any AI and machine learning in healthcare is whether the insights they yield are useful and usable, what effects the use of those insights could or does have, and the extent of those effects. Only integer programming would make it possible to give definitive performance measures; it is unlikely that anyone would benefit greatly from that. The capacity for integration into clinical workflows will define how impactful NLP might be in any given healthcare setting. That sort of integration also demands systemic changes. This paper perceives healthcare systems in which it might make sense to use NLP. Acknowledging and addressing the disadvantages of NLP in healthcare should make the net positive effects of its use more durable and robust.

5.2. Overview of Natural Language Processing

Natural language processing (NLP) currently holds a prime space in the field of artificial intelligence and machine learning. Understanding human language is an extremely complex task, and it involves using sophisticated algorithms and intricate machine-learning models. On the surface, this means that NLP enables machines to analyze any piece of text, but in reality, NLP is so much more. Language models, which are an integral part of NLP, carry out a variety of functions. They can summarize, translate, interpret, and even generate human-like text. In a healthcare scenario, this could even mean chatbots interacting with patients, where natural conversation helps soothe a troubled mind. But this is not without its complexities. NLP is an interdisciplinary field that combines work from different domains like linguistics, computer science, and artificial intelligence. NLP is used to query databases of text, where humans on the other end are asking complex questions, which further underscores the capabilities of NLP. Although it can be applied to a wide range of contexts, NLP technology often has various limitations, especially in understanding and processing contextual subtleties in human language. The language, whether it is written or spoken, often carries context and subtle hints, especially in idiomatic expressions, that are not understood by machines, leading to machines adopting a literal approach that may misinterpret or misunderstand the text. This limitation of general NLP has also been reflected in healthcare NLP. In healthcare, the subtlety of human conversation is further compounded by the complex lexicon that is used in medicine, which includes new terminologies, synonyms, and jargon that are often not recognized by a general NLP-based engine. Then there is the need to even understand the implicitness and the ambiguity in human utterances, another aspect mostly failed at by general NLP. This necessitates the need to customize NLP for healthcare and medicine. In a typical healthcare system, the electronic health record (EHR) includes a wealth of patient data stored in the form of free text. NLP algorithms can help convert unstructured data to structured data and analyze the structured data to derive some new insights, which could assist in improving clinical care or patient outcomes.

5.2.1. Definition and Scope

Natural language processing (NLP) is a field of computational linguistics at the intersection of artificial intelligence. As a scientific field, it is concerned with the design of models and algorithms that enable computers to interact effectively with human language. NLP is also an engineering discipline, involving a planned and quantitative approach to the development of such systems. Many techniques and applications fall under the umbrella of NLP, including text analysis, tokenization, named entity recognition, sentiment analysis, question answering, summarization, clustering, translation, and machine translation. While the task of mapping from written or spoken messages into one of a finite set of integrated requests and/or responses is quintessentially computational, it is not merely symbolic nor logical: an essential part of it is fundamentally linguistic.

The data generated by healthcare systems are exclusively unstructured, to the extent that even some types of structured data, such as laboratory test results, are so far removed from their interpretation in the medical record that they may as well be expressed in natural language. Furthermore, some of the most important data relating to an individual's encounter with the health system are contained in unstructured formats – clinical notes written by physicians or transcribed from dictation, and increasingly, patient narratives or other social determinants of health. NLP is concerned with the use of computers in the analysis and synthesis of natural language, and doing so in the context of healthcare; in other words, NLP for healthcare. It has many potential uses in areas as disparate as industrial big data, care delivery and outcomes research, healthcare professionals training, clinical decision support, public health, and as a means of improving outcomes in rare conditions. Unfortunately, many within healthcare do not understand its capabilities, believe it must be impenetrably complex, or regard it as having no possible application to their data until some hypothetical future point at which it may exceed human performance (Nampalli, 2022).

Equation 1 : Word Embedding Representation:

$$v(w) = W \cdot o$$

$v(w)$: Vector representation of the word w,
W: Embedding matrix,
o: One-hot encoded vector of w.

5.2.2. Applications in Healthcare

Organizational applications in healthcare. The requirement for NLP in healthcare is vast, and a lot of research has been done in applying NLP to characteristic use cases in health.

Clinical notes provide rich and comprehensive details about a given individual's medical or health state, and NLP can be used to generate a broad view of the information contained in concisely free-text clinical notes. Physicians spend huge amounts of time making notes of symptoms, diagnosing conditions, prescribing drugs, ordering labs, and doing many other activities that can be captured in progress notes, and the clinical data and decisions are tied to these activities.

Among many administrative tasks that healthcare providers or practice managers may turn over to another worker is billing. To bill a patient or schedule return appointments, coders will inspect a patient's EMR to establish treatment or diagnosis codes. There are other administrative documents associated with hospitals. Admission and discharge reports explain when a patient checks into or out of the hospital. One can further break down the above two classes into subcategories. Each admission/discharge of the patient includes a concept code which is a foreign key to the concept dimension table. Medication or drug administration events have a corresponding class and conceal a concept. The free-text comments are then manually reviewed by annotators. Shortly, when a field expires, the staff are notified and sent over to recapture the information.

The healthcare provider is often the first and principal object of other people's data. In this use case and the following two, the goal is for NLP to support patient-provider interaction and longitudinal notes analysis to personalize care. This case looks at the text in psychiatry and notes that are being physically made by doctors. We assume that this is an unstructured audio file in which therapy sessions are converted to text. Sentiment regarding disease course, social context, comorbidities, severity of symptoms, chronicity of problems, impact of the patient on personal life, variables that made the patient sick, and variables that attenuated sickness, etc., and recorded changes in these elements are also transparent in a psychotherapy note. The note also incorporates reminders of which activities can be done, an assessment of safety, and functionality, and a few abbreviated detail-oriented status features. Because of this, we are naming this tracking questionnaire the collateral status note.

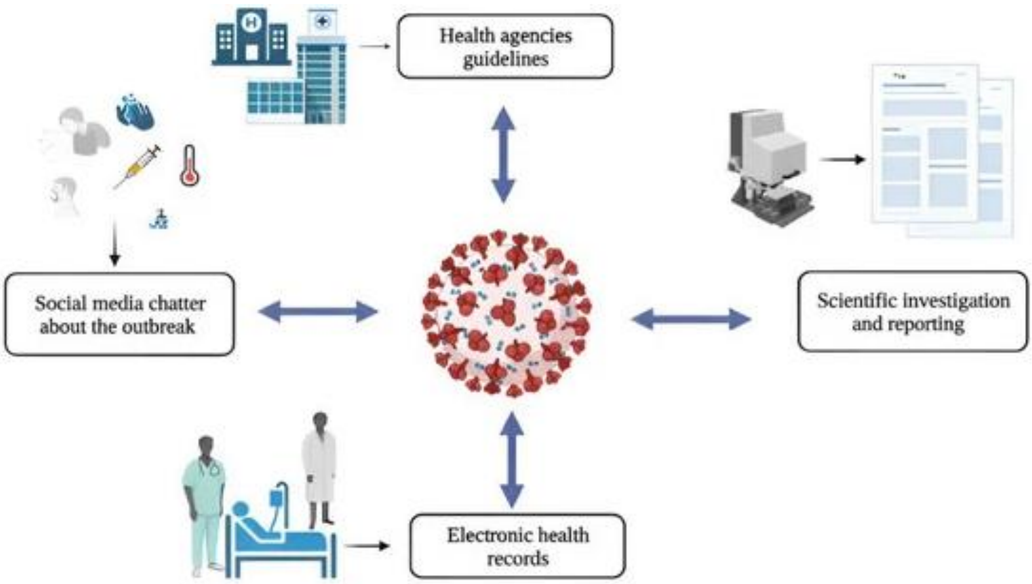

Fig 5 . 2 : The Role of Natural Language in Health Applications.

5.3. Challenges and Opportunities in NLP for Healthcare

Developing NLP tools for healthcare settings has significant potential to advance research and the delivery of care. In this chapter, we outline the challenges and opportunities in using NLP for healthcare and overview some key signal sources and NLP techniques. Clinical data, including electronic health records, scientific literature, and public datasets, are ways that practitioners in natural language processing can accurately forecast diagnoses, diseases, drugs, and other phenomena associated with patients' data. While these applications may sound familiar to practitioners in other medical science, research, and policy domains, explicit explanations do not necessarily accompany discussions of model development, validation, and use (Ramanakar, 2024). Data in the medical and clinical domain differ from that of other natural language tasks, having been collected for a specific purpose.

NLP research groups and centers continue to grow in numbers and prestige. The rapid burgeoning of NLP is largely being advanced by increasing research areas and applications, many of which are related to technological advances that enable simultaneous data analysis and acquisition. The ability to offload the tedium of data analysis onto automated systems has led to a relative increase in the sophistication and diversity of NLP methods. These methods also enable simultaneous data analysis and acquisition. Whether from social media, photographs, or other documents, recent NLP research tools enable researchers and practitioners to crawl for new datasets that feed into their analyses and model development efforts. However, these successes have only partially translated into healthcare settings due to certain data being largely out of reach, including protected health information and other difficult-to-obtain signals.

5.3.1. Data Privacy and Security

The clinical nature of health information collected from individuals poses challenges for its use in defining NLP health tasks. Particularly, patient health data has been strictly regulated through legal and contract terms to ensure data privacy and security. Health NLP work must integrate with the requirements of clinical health information. A core requirement for any health NLP approach development in the clinic is compliance with numerous policies, laws, and regulations governing the usage of patients' health data.

Natural Language Processing (NLP) researchers have a deep interest in learning from potentially large amounts of patient health data collected in electronic health records by exploiting NLP algorithms. Electronic health records are particularly interesting due to the wide range of English and non-English language modalities used in their contents and their resulting unstructured nature. Extracting useful diagnostic and prognostic data from electronic health records with NLP has led to several solutions that are of great interest in healthcare and other domains. However, the clinical nature of electronic health record data poses unique challenges for the development and evaluation of NLP algorithms. We review in this report clinical NLP issues such as the use of protected health information for external training and testing, technical jargon, and portability of trained NLP models. The primary focus is on NLP from clinical data that abounds and how insights obtained from electronic health records can be used to better understand or augment our knowledge.

Fig 5 . 3 : Natural Language Processing in Healthcare

5.3.2. Integration with Electronic Health Records

Electronic health records (EHRs) contain patient health information that is frequently stored in a semi-structured and unstructured format. NLP allows information stored in these documents to be extracted for analysis. Insights gained from EHR data via NLP have wide-ranging applications, including automating patient diagnosis and prognosis, treatment and administration, and personalized medicine, as well as supporting timely clinical decision-making. Information, such as symptoms, key clinical findings, medication, treatment, complications, and timelines, are frequently recorded in free text format in EHRs or clinical notes. A patient's chief complaint might be a few sentences of free text about what brought him or her to the hospital, and physicians generally dictate or manually type visit summaries for each patient visit (Syed, 2022).

However, the fragmented, semi-structured nature of EHR data might make the attempt to use it for clinical analytics challenging. Using NLP to streamline the conversion of clinical notes into a computable knowledge bank has gained significant traction in the field of clinical informatics. Properly managed NLP pipelines allow the large-scale transformation of vast quantities of clinical notes originating in hospitals into structured information that enables researchers to address myriad types of questions.

5.4. Case Studies and Examples

Once limited to conceptual exercises or academic curiosity, field-leading organizations and institutions continue to demonstrate important, tangible successes in applying natural language processing innovations to real-world applications in healthcare. Case studies and prior examples of NLP in healthcare settings evidence a wide variety of significant impacts in a diverse array of areas, such as improving patient care, patient experience, and clinical process efficiency. Sentiment analysis, powered by NLP technologies, has been harnessed to help organizations better understand their patients and adjust services accordingly. Automatic sentiment analysis has become important in the healthcare industry as hospitals strive to make sense of feedback from patients submitted via letters, forums, or social media. Researchers and organizations providing additional attention to sharing their NLP success stories will help other institutions innovate by joining the dots between an innovative academic paper and a tangible commercial product. Several large, notable companies have provided research software. These standalone tools can be used to help teams that have limited experience with machine learning or NLP technologies extract valuable clinical insights from medical records and simplify the development of healthcare AI applications. It is worth noting that when sharing case studies in this manner, it is critical to separately partition development, validation, and testing datasets to offer evidence of robust, reproducible performance.

5.4.1. Sentiment Analysis in Patient Feedback

Patient feedback is a strategic asset to improve both clinical and non-clinical service delivery. Beyond the standard feedback elicited through formal surveys, comments and feedback are continually being made across a range of social media, internet-based consumer review platforms, and internal feedback systems. This reveals an untapped trove of unstructured qualitative data waiting to be analyzed to better understand societal, cultural, and language-specific patient experiences. Feedback is first-hand empirical evidence of the lived consumer or patient experience. Sentiment analysis is situated within the field of natural language processing. This analysis allows computers to better understand human language. The principal algorithms being used in healthcare are computer-assisted structured queries, textual predictive algorithms, or predictive data analytics engines. These systems provide quantifiable insight into patient experiences by analyzing the language used in the feedback to gauge the emotional experience and the net promoter sentiment based on the overall tone.

Indeed, the unstructured text comment represents invaluable patient-centered qualitative data, providing a rich source of the usual 'what', 'how', and 'why' that lie behind the scores derived from structured quantitative data. Patients are afforded the valuable opportunity to express their thoughts in their own words to such survey questions as 'Is there anything else you would like to tell us about your overall experience?' Perhaps the most frequent implementation of sentiment analysis in a healthcare setting has been in emergency medical care. An analysis of free-text feedback in the NHS dental contract patient experience survey found that the addition of textual sentiment and thematic analysis of free-text comments provides a much richer appreciation of patient experience than quantitative data alone; explicitly revealing issues that would otherwise be considered to be of low priority. Challenges associated with sentiment analysis in healthcare are significant (Tulasi et al., 2022). Synonyms and the heterogeneity of language and expressions used across socio-cultural demographics pose practical challenges. Rare language-use phenomena may further exacerbate the subtlety needed to reliably process healthcare opinions from patient feedback. As the speaker demographic differs markedly for chronic and healthcare short-stay patients, it requires a balanced effort from service advisors. Furthermore, the language used in healthcare feedback may not be familiar to all advisors, as a large proportion of the workforce may not have worked extensively in health and care. A policy may, therefore, be needed to keep the patient's language as inclusive and general as possible. It is a fallacy to acutely ignore any mandated national or state-based additives that may appear in national surveys where the questions intermingle, namely global citizenship, with sociology constructs typically in private data collection environments. In essence, the more diversity in a system, the more challenging the system. When the evidence points to patient experience being directly linked to health outcomes, dare we argue that this mandates investment in all things pivotal to patient experience, and sentiment is certainly a patient-centric and crowdsourced perspective.

5.4.2. Named Entity Recognition in Medical Reports

Named Entity Recognition (NER) is a natural language processing task that is applied to medical text in a clinical browsing context called Medical Natural Language Processing. It consists of identifying key “entities,” i.e., a specific term or a “chain” (i.e., a sequence of terms such as “acute myocardial infarction”) that refers to a proper entity that resides in the medical domain. Typical entities addressed in NER studies applied to medical reports include the names of diseases, clinical findings, tests, treatments, medications, apparatuses, general and family history, measurements, subjects and/or subjects’ characteristics, and so on. Being able to accurately identify such terms out of an unstructured clinical narrative inputted into computers both enhances information retrieval and supports decision-making. The extraction of unstructured named entities also streamlines the registration of structured data in a patient’s electronic health record to support easier research and analysis operations.

Several case studies focusing on a variety of acute and chronic diseases within different hospital settings and healthcare organizations and addressing NER applied to radiology, pathology, and discharge notes, observation records, or nursing documentation report NER’s potential to organize and interpret clinical notes automatically. The NER task, at the same time, presents challenges in dealing with the automatic extraction of concepts from free text containing several unknown abbreviations, acronyms, and medical jargon; related to the recognition of a reported attempt or refusal to declare relatives’ illnesses or medications and the distinction between a positive and negative result; the recognition of various types of family/social history, i.e., the chronic conditions of the immediate family, particular diseases of the female’s mother, pregnancy-only family history, and other family disease-specific details. For those reasons, machine learning-based methods, including named entity recognition, are under investigation employing deep learning approaches involving the use of advanced computational models. Research addressing NER methods in the medical field is still ongoing, as there exist future options for leveraging such capability in combination with other tasks in the context of population health management for predictive analytic models (Venkata et al., 2022).

Equation 2 : Sequence Modeling (RNN/LSTM):

$$h_t = f(h_{t-1}, x_t; \theta)$$

h_t: Hidden state at time t,

h_{t-1}: Hidden state at time $t-1$,

x_t: Input at time t (e.g., word vector),

θ: Model parameters,

f: Activation function (e.g., tanh, sigmoid).

5.5. Future Directions and Conclusion

Future Directions Many healthcare settings have vast archives of data in both structured and unstructured formats. Emerging technologies, such as deep learning, hold the promise to further enhance the capabilities of NLP to automatically extract information from large collections of clinical documents. The wider use of techniques from the biomedical NLP community comes in sync with trends in healthcare toward value-based care. NLP is well placed to support research and policy changes that will further realize the value of administrative and clinical data that are available electronically. For example, clinical document synthesis or automatic curation of rare disease registries from rare disease patient encounters in free text, diagnostic areas that benefit from patient-confirmed information. In many ways, the sky is the limit, but only with interdisciplinary involvement will the challenges of adaptation, optimization, and validation be met. Some potential future directions are listed in terms of the opportunities opened, the challenges posed, and the needs presented (Pandugula et al., 2024).

While there are ongoing technical developments and conceptual re-evaluations of NLP entities, we are renewing speculation about what roles NLP will play within healthcare settings in the immediate or near future. Having delineated some instances in which NLP has shown promise, we must emphasize that for these possibilities to be concretely realized, NLP will be redesigned and revalidated. Multi-site longitudinal investigations are useful functions, but ones that inspire changes to the NLP formulation are both theoretical results and epidemiological ones. Finally, tracing the evolution of NLP entities that are no longer stable but may variably function as predictor variables, valid false-negative examples, or generation propositions, as well as producing incompletely mature induction-based outcomes that to some degree approximate volatile background rates, has led us to advocate for 'the full NLP,' a blend of historically separate conceptual bodies. Having traveled this far, there is cause for optimism.

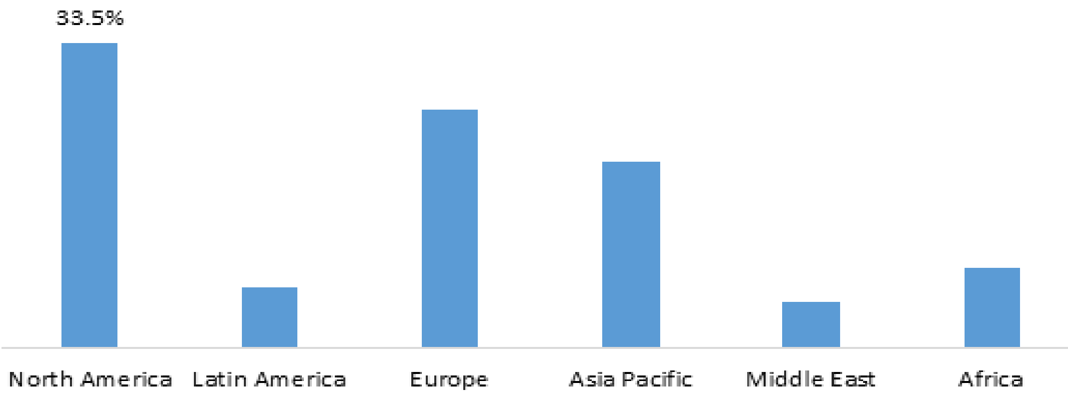

Fig 5 . 4 : Natural Language Processing (NLP) In Healthcare.

5.5.1. Emerging Technologies

Several emerging technologies have the potential to enhance and enable NLP in healthcare settings. There continue to be improvements in machine learning algorithms, including the library of pre-processing and processing steps, automatic facial recognition in digitized images, and algorithms for interpreting naturalistic datasets. Moreover, within the class of machine learning methods, there have been several advances in deep learning frameworks for interpreting text and speech, with specific advances in areas such as word sense disambiguation and gap filling. These can be beneficial for both generating cohesive pieces of human language and interpreting poorly written or unintelligible data, particularly from older adults or individuals with aphasia. Emerging trends for the integration of NLP are in the use of these methods in combination with other technological advancements. These include the integration of NLP with emerging areas of interest such as telemedicine and wearable health devices, to produce more cost-effective, efficient, and personalized approaches to providing care. In the research sector, there has been interest in the application of real-time data processing and predictive analytics to healthcare data, which allows for outcomes-based medicine. This combined approach could allow for better patient outcomes by sharing data when the time is right for the appropriate provider, and the appropriate outcomes-based algorithm can be triggered discreetly. Mass marketing to individual patients and consumers may be a tactic of the past as telemedicine hinges its methodology on narrower predictive analytics and less costly personalized patient care. The main driving forces for the mass application of these trends are aimed at serving several needs, including getting appropriate individuals in early, optimizing technology utilization, and connecting to groups that are both powerful and technologically sophisticated: youth and the geriatric populations. Lastly, for these developments to come to fruition, there must be ongoing development, validation, and experience with these tools and technologies (Kalisetty et al., 2023).

5.5.2. Ethical Considerations

Data privacy and patient consent are two significant ethical concerns. Collecting sensitive data from diverse sources of a patient's life requires obtaining informed consent. Ethics regulations require informed consent for data processing of patient records. Because of the tremendous variety of the data that are processed for NLP research in healthcare, it is often infeasible to obtain informed consent. Although these regulations allow for the processing of patient data, they set strict security and privacy standards for those using the data. Therefore, NLP researchers must engage in transparency and ethical processing practices. A contentious issue is the form that algorithmic bias can take in NLP technologies. Biased datasets can result in a biased prediction model, with dangerous consequences. For example, the lack of representative data on non-white populations can lead to adverse outcomes for these populations.

Efforts to make the outputs and inputs of prediction models interpretable rather than merely as complex inputs and outputs have specific ethical implications: ensuring that the outputs align with real-world data, efforts must be made to ensure that the processes for identifying biases in inputs and predictions are both fair and ongoing. For example, recurring evaluations of prediction models to determine if they continue to unfairly benefit one group at the cost of another is an ethical benchmark. A recommended course of action is to establish ethical guidelines and frameworks for creating NLP technologies whose outputs benefit the diverse populations these technologies aim to serve (Sondinti et al., 2023). It is also recommended that data handling processes be continually updated and open to public feedback. Mandatory transparency in the algorithm, model, and presentation specifics is a crucial criterion for creating ethical NLP technologies. Important concerns regarding the creation of an ethical NLP workload are coping with the possibility of some outcomes being harmful. Ethical NLP stakeholders must go beyond considering the outcome of specific technology solutions to consider the potential effects of bias in NLP research processes. They should involve stakeholders in these conversations, especially in the dissemination of their research constituency. Best practices are also recommendations for engaging with vulnerable communities, such as those with low English literacy. This engagement might include providing accessible visual materials, engaging community organizations, advocates, and local subject-matter experts as advisers, and promoting dialogues between those who directly will benefit and be affected by the NLP technology. Researchers have emphasized the importance of committing to a continuous updating of algorithms and data handling processes. They identified the effectiveness of communally reinforcing ethical NLP commitments and accepting public feedback that aligns with these commitments as essential. They highlighted the importance of working in concert with both the public and especially those potentially adversely affected when establishing an NLP ethics framework.

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