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SURVEY

Clinical Errors From Acronym Use in Electronic Health Record: A Review of NLP-Based Disambiguation Techniques

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ABSTRACT The adoption of Electronic Health Record (EHR) and other e-health infrastructures over the years has been characterized by an increase in medical errors. This is primarily a result of the widespread usage of medical acronyms and abbreviations with multiple possible senses (i.e., ambiguous acronyms). The advent of Artificial Intelligence (AI) technology, specifically Natural Language Processing (NLP), has presented a promising avenue for tackling the intricate issue of automatic sense resolution of acronyms. Notably, the application of Machine Learning (ML) techniques has proven to be highly effective in the development of systems aimed at this objective, garnering significant attention and interest within the research and industry domains in recent years. The significance of automating the resolution of medical acronym senses cannot be overstated, especially in the context of modern healthcare delivery with the widespread use of EHR. However, it is disheartening to note that comprehensive studies examining the global adoption of EHR, assessing the impact of acronym usage on medical errors within EHR systems, and reporting on the latest trends and advancements in ML-based NLP solutions for disambiguating medical acronyms remain severely limited. In this current study, we present a detailed overview on medical error, its origins, unintended effects, and EHR-related errors as a subclass of clinical error. Furthermore, this paper investigates the adoption of EHR systems in developed and developing nations, as well as the review concludes with an examination of various artificial intelligence techniques, particularly machine learning algorithms for medical acronym and abbreviation disambiguation in EHRs.

INDEX TERMS Medical NLP, health informatics, artificial intelligence, EHRs, computerized health records, word sense disambiguation.

I. INTRODUCTION

Acronyms and other types of word abbreviation are compelling in usage and gaining traction in the clinical domain. One of the motivating factors behind the widespread usage of acronyms and abbreviations among physicians is the rapid adoption of the Electronic Health Record (EHR) systems in clinical settings. This electronic version of patient health history often contains all important administrative clinical data relevant to a patient's care and is maintained by healthcare providers over time. EHR provides a digital format for a patient's paper medical chart. Unlike traditional paper

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records, EHRs offer real-time, patient-centric records that can be securely accessed by authorized users. In actual fact, most health reports are now written at the time of service by doctors who type, dictate (using speech recognition software), enter notes into a semi-structured or templated document entry system, or utilize a combination of these approaches [1]. However, these shorter word forms frequently have multiple various meanings (i.e., ambiguous), and thereby making automated or semi-automated extraction from notes difficult. Moreover, they also pose several communication challenges, which are capable of jeopardizing the patient's safety [2], [3], [4].

It is of utmost importance to accurately decipher and provide the intended sense or full form of acronyms and other abbreviated word forms commonly found in clinical reports. This task is just as vital as comprehending the overall content of the document. With the proliferation of acronyms and their multiple meanings, as highlighted in numerous studies [2], [4], [5], [6], [7], the issue of acronym ambiguity is widely acknowledged as a significant challenge that impacts effective communication in the medical field. Traditionally, making sense of acronyms and other confusing language has been a matter of human perception and interpretation. However, the increasing usage of clinical acronyms due to extensive adoption of EHR systems presented a new challenge for researchers: developing and improving an automated sense resolution technique for medical acronyms and abbreviations in clinical notes. While it is much easier for human (i.e., expert) readers to derive the intended meaning of an acronym or abbreviation based on the context of usage in a sentence, it remains very challenging to automate the process, due to several challenging factors.

The development and implementation of automatic algorithms for medical acronyms and abbreviations sense resolution in clinical notes such as EHRs is an important topic in medical NLP, and it is regarded as a subset of Word Sense Disambiguation (WSD). The task of automating the resolution of intended sense of acronym and abbreviation in clinical note primarily involves teaching a computer program to accurately provide the intended complete meaning of the acronym based on the context of its usage in the document. To assist knowledge-based applications like error detection, decision support, as well as surveillance, a variety of Natural Language Processing (NLP) algorithms have been presented to obtain patient health information from narrative health records.

However, existing automated medical NLP approaches still suffer several challenges, which could be attributed to a paucity of complete inventories of acronyms and their various senses (sense inventory), as well as the dearth of effective methods for disambiguating abbreviations with numerous senses [8]. With the advancements of modern machine learning (ML) technologies, several domain-specific medical problems, such as disease detection [9], [10], mortality prediction [11], [12], [13], [14], and patient monitoring [14], [15], [16] have been successfully addressed. As a result, numerous authors have been encouraged to explore the enormous potential of various ML algorithms for the automation of clinical text extraction and medical acronym disambiguation. While several authors have contributed various comprehensive reviews of existing research studies in the field of medical NLP over the years (as evidenced in Table 1), there is scarcity of studies that provide a comprehensive and structured overview of medical errors stemming from acronym use in EHR. Specifically, studies that encompass the extent of EHR adoption, the challenges associated with it, and provide a critical assessment of current trends and advances in machine learning-based NLP solutions for automated sense resolution of acronyms and abbreviations in clinical notes.

In this study, we offer a comprehensive overview of medical errors, including their unintended consequences, with a specific focus on EHR-related errors as a distinct subclass. Additionally, we delve into the adoption of EHR systems in both developed and developing countries, examining implementation challenges and issues in each region in detail. In addition, we have performed a literature review focusing on NLP algorithms that can automatically disambiguate clinical acronyms and abbreviations within EHRs. Our review encompasses articles published between 2012 and 2023. To sum up, we highlight recommendations and future research directions. The unique contributions of this study can be summarized in fourfold:

1. We contribute a comprehensive and structured overview of medical errors, their origins, unintended effects, and EHR-related errors as a subclass of clinical error.
2. We investigate the adoption and implementation profundity of EHR systems in developed and developing nations, as well as identify various implementation and usages challenges.
3. This article examines various machine learning algorithms for medical acronyms and abbreviation disambiguation in EHRs.
4. Various issues and challenges for the development of accurate NLP tools for automatic acronyms disambiguation were discussed, future research trajectories were also identified.

The remainder of this paper is organized into sections. Section II presents a detailed overview of errors in medical practice. Section III describes EHR, its adoption in developing countries, and the issues and challenges encountered. In Section IV, we review previous work applying AI for acronyms disambiguation in clinical notes. In Sections V and VI we discussed our findings and concluded the paper.

II. OVERVIEW OF MEDICAL ERROR

Medical error is a serious issue in public health because it is difficult and time-consuming to identify all consistent causes of errors. It is widely regarded as one of the most critical threats to patients' health [24]. According to the Institute of Medicine's report on healthcare safety, To Err is Human, approximately 98,000 Americans die each year from avoidable medical errors [25], [26]. Correspondingly,

TABLE 1. Existing survey articles on clinical acronyms disambiguation.

Paper title	Limitations	Authors
Word Sense Disambiguation in the Biomedical Domain: An Overview	▪ the review is limited to biomedical domain. ▪ only studies on WSD with statistically based algorithms are review.	Schuemie et al. [17]
Machine learning and word sense disambiguation in the biomedical domain: design and evaluation issues	▪ limited to supervised machine learning (ML) methods for WSD. ▪ only literature on abbreviations use in biomedical domain were reviewed.	Xu et al. [18]
A comparative study of supervised learning as applied to acronym expansion in clinical reports	▪ restricted to supervised machine learning (ML) methods for WSD. ▪ considered methods employed in assessing information in clinical reports alone.	Joshi et al. [19]
Word sense disambiguation across two domains: biomedical literature and clinical notes	▪ the study considered just supervised machine learning (ML) methods for WSD ▪ unlike most studies, it considered papers on both clinical and biomedical domain.	Savova et al. [20]
Knowledge-based biomedical word sense disambiguation: comparison of approaches biomedical domain.	▪ the studies considered are limited to knowledge-based approaches ▪ the studies are limited to biomedical domain	Jimeno-Yepes et al. [21]
Determining the difficulty of word sense disambiguation.	▪ limited to ambiguous biomedical terminologies alone.	McInnes et al. [22]
Clinical text data in machine learning: systematic review	▪ only the text data features utilized for training machine learning approaches to clinical NLP are investigated	Spasic et al. [23]

a 2006 report by the Institute of Medicine of the National Academies further revealed that medication errors affect at least 1.5 million individuals annually, making them one of the most frequent types of medical errors. Report states, the cost of treating drug-related injuries in hospitals alone amounts to \$3.5 billion per year, exclusive of lost wages and productivity or additional healthcare costs [27].

In its executive summary released in the year 2000, the National Academy of Medicine, which was then called the Institute of Medicine, defined error in clinical and medical practice as ''the failure of the planned action to be completed as intended (omission) or the use of the wrong plan to achieve an aim (commission)''. Despite efforts to reduce medical errors, they remain the primary cause of harmful patient incidents and a significant financial liability for healthcare systems worldwide. Patient injury resulting from unsafe medical care is globally recognized as a leading cause of morbidity and mortality [28], [29], [30]. The World Health Organization defines patient injury as ''an incident that results in harm to a patient, such as impairment of structure or function of the body and/or any adverse effect arising therefrom or associated with plans or actions taken during the provision of healthcare'' [31].

Patient injuries caused by medical errors can manifest at both the individual and system levels [32], [33]. These injuries may result from an unintended act (omission or commission) or an action that does not achieve its intended outcome [34], [35]. They can also be caused by the failure of a planned action to be executed as intended (an error of execution), the utilization of an incorrect plan to achieve an aim (an error of planning), or an aberration from the process of care [32].

Over the years, the error taxonomy in the clinical domain has continued to evolve, becoming more comprehensive and precise in categorizing factors and events that can be prevented. This evolution has been driven by the need to account for variations in measurement techniques, variables, and detection methods, and study populations. Moreover, the absence of an internationally standardized taxonomy that describes what constitutes an error, potential error, or error cause is also a reason for the growing taxonomy [36]. In Figure 1, we present the taxonomy of error in medical practice proposed by [37]. In this figure, two major error causes are identified, and medical errors at the individual level are further classified into four main categories: medication error, diagnostic errors, treatment errors, and clinical errors. Each of these categories is further subdivided into subcategories that describe the types of errors that can occur. This taxonomy helps healthcare professionals recognize and prevent different types of errors that can occur at different levels of medical healthcare delivery.

A. COMMON CAUSES OF ERROR IN MEDICINE

The most common and preventable cause of patient injury is medical error, with potential causes including incorrect medication, incorrect administration route, and incorrect medication time [24], [38]. Some errors are unintentional, such as those caused by misunderstanding or miscommunication [39]. Furthermore, medical errors can be complicated; some are insignificant, while others can take the life of a patient with a long-life expectancy [32]. Thus, it is not surprising when some research findings [32], [40] revealed that, after cancer and heart disease, medical error is the third leading cause of death in the United States. Several other studies on medical errors show that the causes of medical errors include medication errors, diagnoses errors, surgical errors, therapeutic errors, procedural errors, never-happen events, facility accidents, hospital acquired infections, referral errors, error of uncoordinated care, missed warning signs, and untimely discharge from health facility [24], [38], [41]. In Table 2, we provide a comprehensive list of common types of medical error and their potential causes as discussed in previous literature.

While medical errors continue to be a major hazard to patients' well-being, their victims far exceed the patient [40]. In the occurrence of errors in healthcare, four groups are impacted in a domino effect: the patient and family (first victim), healthcare personnel (second victim), hospital reputation (third victim), and patients who are affected as a result (fourth victims). Safe, dependable, and patient-focused care is crucial and paramount as the main and ultimate goal of medicine. To reduce the occurrence of medical errors, the use of electronic health records (EHRs) and other e-Health systems have been promoted as possible methods.

B. EHR-RELATED MEDICAL ERRORS AND SAFETY CONCERNS

The adoption of EHR systems has significantly reduced medication and a few communication-related errors, but its performance in reducing diagnostic and technology-related errors has not been particularly encouraging or promising [64]. It, however, produces a new type of communication-related error as healthcare information technology, which

TABLE 2. Common causes of error in medical practices.

Type	Common Causes	Reference
Medication errors	Inappropriate use of medicine	[38-43]
	Prescription of wrong medicine	[38, 44]
	Failure in double-checking procedure	[42]
	Low level of Knowledge about use and administration of medications	[36]
Surgical errors	Inadequate education and training of surgeons	[24, 45, 46]
	Significant communication breakdown between the anesthesiologist, the surgeon, and the supporting staff.	[47, 48]
	Hasty case completion	[49, 50]
	Utilization of faulty systems or protocols	[49, 51]
	Miscommunication between the patient and the surgeon	[48, 52]
Diagnostic errors	Inappropriate test request	[53]
	Order entry mistakes or delay	[54-57]
	Incorrect interpretation/utilization of diagnostic/laboratory tests result	[53, 58]
	Sample handling, identification, storage and transportation issues	[53, 59]
Therapeutic errors	Wrong drug-drug interaction or duplicate medication	[38, 60]
	Incomplete or unclear medical prescription	[38, 60]
	Incorrect interval	[38, 61]
	Overdose/underdose	[38, 61-63]
Procedural errors	Lack of proper training or experience	[38, 42, 43]
	Poor communication among healthcare provider and distractions	[38, 44]

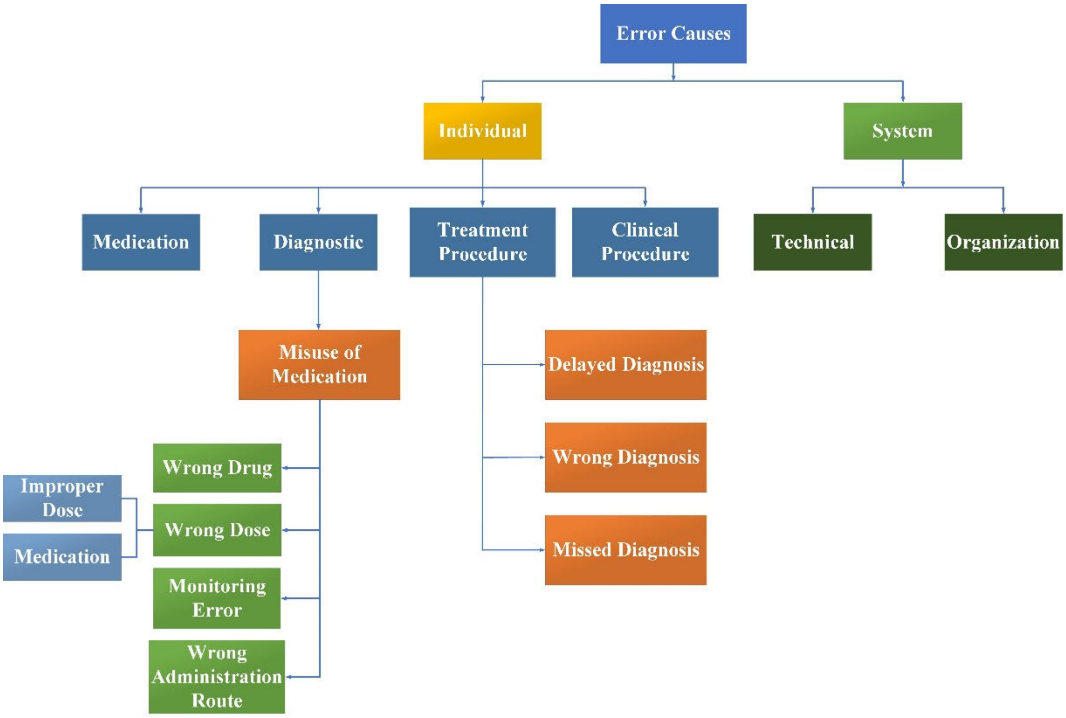

FIGURE 1. Taxonomy of errors in medical practice, which classifies error causes into two main categories: individual errors and system errors. Within the individual errors category, errors related to medication, diagnosis, treatment procedures, and clinical procedures are included. Technical and organizational errors, on the other hand, fall under the system errors category.

TABLE 2. *(Continued.)* Common causes of error in medical practices.

	Time pressure and fatigue	[38, 44]
	Complexity of procedure and poorly designed processes	[38, 44]

may occur during interaction with the system, information retrieval, and decision making. Although the use of clinical acronyms and abbreviations is not new in medicine, it becomes more pervasive with the adoption of EHR. While abbreviations were once limited to prescription writing, they have already become quite popular in many parts of medical reporting. During surgery, in the emergency room, and at the time of discharge, medical abbreviations are utilized across all medical and surgical departments [65].

A common application zone in which medical abbreviations are frequently employed, and cause concern, is when drafting prescription orders. However, the over utilization of abbreviation in a flaw-prone system like EHR, with insufficient backup to detect errors, increases the risk of conceivable mistakes at some stages of prescription order interpretation and/or drugs dispensing by practitioners. Among the most significant implications of EHR-related errors is patient safety. Errors such as incorrect medication dosages, missed diagnoses, or delayed treatment plans can have harmful effects on patients, including adverse reactions, complications, and even death. The complex nature of EHR systems and the potential for human error can contribute to these errors, making it crucial for healthcare providers to remain vigilant and attentive to their use of these systems.

Moreover, EHR-related errors can also have a broader impact on healthcare outcomes. They can lead to unnecessary healthcare costs, wasted resources, and inefficiencies in care delivery. For example, incorrect information in EHRs can lead to duplicate tests, procedures, and prescriptions, increasing healthcare costs and reducing the quality of care. EHR-related errors can also contribute to the fragmentation of care, making it more challenging for providers to collaborate effectively and provide coordinated care.

Finally, EHR-related errors can also affect the trust patients have in their healthcare providers and the healthcare system as a whole. Patients rely on their providers to accurately record and interpret their medical information, and any errors can erode this trust and negatively impact patient satisfaction and engagement. In conclusion, EHR-related errors can have significant implications for patient safety, healthcare outcomes, and the healthcare system. Understanding the information flow and reduced similarity of these errors can aid in the development of effective strategies and tools to prevent and address these errors, enhancing the quality of healthcare and patient outcomes.

C. UNINTENDED CONSEQUENCES OF EHR-RELATED MEDICAL ERRORS

Until recently, the usage of abbreviations was still unregulated, and there is no general law dictating which abbreviations can and cannot be used. Concerns relating to patient safety from use of ambiguous medical abbreviation can broadly be classified as adverse events that affected the patient, near misses that did not affect the patient, or unsafe events that bring up possibility of a safety incident [8]. Moreover, several other unintended consequences and medical errors also emerge as a result of EHR adoption-related technological and socio-technical difficulties, such as usability challenges, disruptions in clinical processes, and dangerous workarounds to circumvent technology-related constraints [66], [67], [68]. EHR-related safety issues are difficult to detect and address because they are frequently multidimensional, involving not only potentially harmful EHR technological elements but also EHR user behaviors, organizational characteristics, as well as policies and guidelines to follow for EHR-related activities. To address the challenges of EHR-related patient safety, comprehensive and more recent ''socio-technical'' methods that account for these components are required [69], [70], [71].

Using an eight-dimension socio-technical conceptual model, [69] analyzed technical and non-technical dimensions of safety in order to identify and evaluate both new and recurring EHR safety issues found in multiple reports. The study's findings revealed that EHR safety concerns were caused by both unsafe technology and unsafe technology use. Also, in a study that aims to find out what types of EHR-related incidents have happened so far and how they are categorized, the authors in [70] found that the error categories may also entail non-technical issues and may not just concern the technology features of the EHRs.

In a similar vein, according to a national survey conducted by [72] on safety, quality enhancement, and healthcare administration officials, health information technology — more specifically, EHR systems — safety and performance were identified as the most worrying dangers in 2013. The number of deaths caused by mistakes that could have been avoided is still going up, and the recommended information technology (IT) fix has revealed a new mistake. This prompts Rajasekar in [64] to ask, ''Is healthcare-IT a knight, a knave, or a pawn?''. Because of how quickly EHRs are being adopted and how ubiquitous acronyms are becoming in such systems, there are concerns about how information will be extracted in the future, which could put patient safety at risk. In summary, medical error remains one of the greatest concerns in clinical settings, as evidently shown in various reports considered in this study as well as their expanding taxonomy over the years.

This error has numerous possible causes and often occurs as a result of omission or commission during healthcare delivery. Among other causes of medical error, miscommunication error is the most frequently occurring one. Since the primary focus of medicine is patients' rights to safe, trustworthy, and patient-centered care, several measures have been adopted in the practice to reduce or possibly eliminate the occurrence of error in medical practice. Among these measures is the adoption of EHRs and other e-Health infrastructure. While the adoption of EHR makes the use of medical abbreviation more ubiquitous, it however, compounded the long-standing concern about its rampant usage and the associated danger to patients' safety.

EHR-related errors are subset of the wider category of medical errors, that specifically refer to errors or adverse events that result from the utilization of EHRs, such as errors in data entry, documentation, ordering, and retrieval of patient information. EHR-related errors can occur due to a variety of factors, such as system design flaws, user errors, and workflow issues. While several prior studies suggested addressing this ravaging issue in healthcare as part of a comprehensive patient safety and quality improvement program, recent investigations are also exploring the use of technological innovations such as artificial intelligence as a possible solution. In the section that follows, we present an overview of the EHR, its adoption and implementation level in both the developed and developing countries, issues, challenges and opportunities, as well as EHR-adoption and clinical acronyms use.

III. ELECTRONIC HEALTH RECORD

Several healthcare organizations have recently shifted away from traditional paper-based medical report records and toward Electronic Health Record (EHR) systems, in which patients' longitudinal medical information is stored in an electronic format on a data repository. EHR, like other types of electronic health (e-health) infrastructure, uses information and communication technology to digitize and automate healthcare delivery operations and tasks [3]. This quick transition has led to the availability of enormous amounts of clinical records in EHR systems, much of which contains helpful patient data [8]. In addition to the physical space savings brought about by the transition from paper to digital records, EHR has played a key role in improving healthcare effectiveness, fostering decision-making, and improving management [73]. The medical Decision Support Systems (DSS), which support all sorts of healthcare service providers, including doctors, employees, and management, in making decisions, are connected to the EHR system. It facilitates, among other things, quick and precise judgments on billing, diagnosis, and data analysis. It makes it easier to make prompt, precise judgments about things like diagnosis, laboratory tests, invoicing and payment processing, and analysis of data [74], [75]. In Figure 2, we provide an illustration of an e-health infrastructure for healthcare delivery. Various elements of e-health infrastructure were provided that include physician support system, knowledge base system, health management information system, EHR etc.

EHR systems provide multiple user access, sharing, and updating from local and remote locations via appropriate user interfaces and network connections, eliminating the need to retrieve and move paper files from a crowded file room. This technology is used to create and store patient data in an electronic manner. The system collects patient data such as complaints, test orders, prescriptions, diagnosis, and

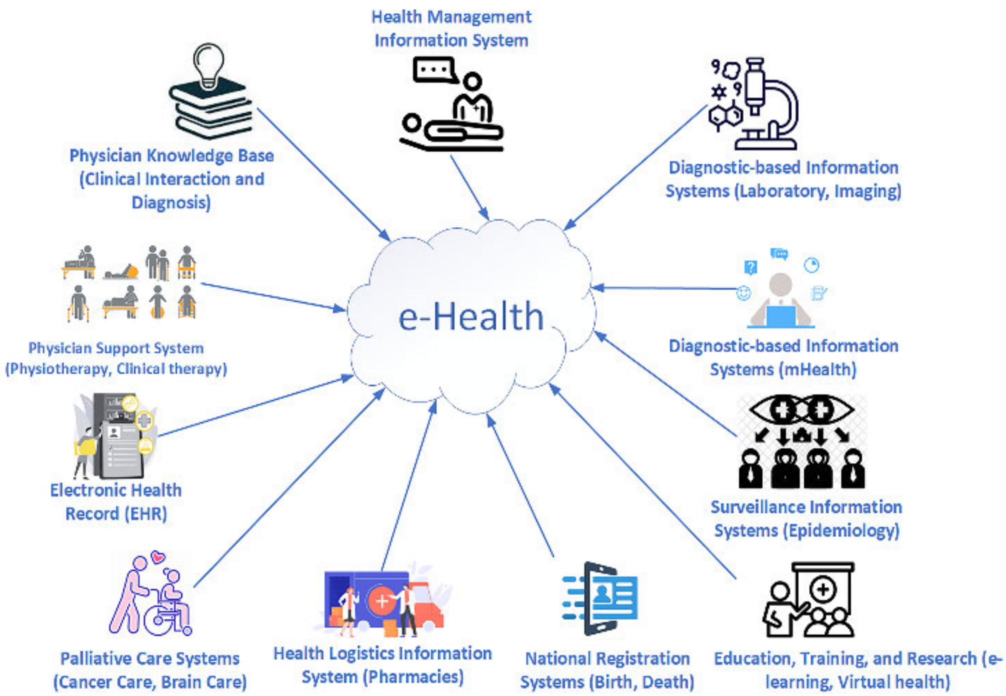

FIGURE 2. Illustration of the different components of E-Health Infrastructure that comprises of various healthcare stakeholders, including physicians involved in clinical interaction and diagnosis, support systems like physiotherapy and clinical therapy, the health management information system, the health logistics system, the electronic health record system, etc.

procedures. This system allows approved health providers to access data gathered, and data can be analyzed, updated, and electronically annotated even if other authorized health providers are utilizing the same patient data [76]. In the medical industry, several NLP algorithms have been employed to find important information in clinical notes in order to improve patient care and facilitate clinical trials [77].

Despite the obvious benefits of implementing these systems, there are significant challenges to overcome when implementing a truly interoperable EHR between primary and secondary care [78], [79]. These concerns are typically associated with the installation process rather than the product of the EHR vendor [80]. As a result, the implementation strategy is critical, and it should be viewed as a continuous procedure that begins with procurement and continues through all phases of design, implementation, testing, installation, and optimization [81]. In the subsequent subsections, we will discuss the challenges and opportunities for EHR adoption and implementation in both affluent as well as low- and middle-income countries. We will also investigate the causes and recommend strategic plans to avoid problems and challenges associated with EHR adoption.

A. EHR ADOPTION AND IMPLEMENTATION LEVEL

Since the mid-1990s, IT capabilities in healthcare delivery have garnered significant attention and financing, particularly in industrialized countries such as the United States, Australia, and the United Kingdom. The shift from traditional paper-based records to EHRs has been uneven and has not followed overall IT trends in several parts of the world. In certain regions, such as Scandinavia and the United Kingdom, primary health care was the first to implement EHR systems, while university clinics at large hospitals pioneered the development in other parts of the world [82]. Despite numerous studies showing the advantages of electronic health records, adoption is still low in developing countries [74], [83], [84], [85]. In fact, many hospitals in developing nations still record patient information on paper [85], [86]. Table 3 shows a few EHR systems that have been implemented and adopted in developing countries.

Due to the belief that the adoption of EHRs can help to improve the quality of healthcare, the use of EHR systems has increased in Europe, the United States, and other developed countries [92]. Nevertheless, there are still issues in the majority of these regions because of healthcare practices and laws, the diversity of regional languages, the emergence of numerous non-interoperable EHR systems, and a lack of or inconsistent clinical documentation in EHR [93]. EHR system creation remains a difficult task that involves a careful match of local needs to available technologies and resources. There is a lack of experience building EHR systems for the developing world; criteria, goals, and local restrictions are likely to be more different [94].

In [95], the authors pointed out that it is difficult to create scalable and functional EHR systems in developing countries and that online access control is necessary for EHRs. Relying

TABLE 3. Some EHR systems adopted in developing countries.

EHR	Country	Year	Reference
Mosoriot Medical Record System (MMRS)	Kenya	2001	[87]
Partners in Health (PIH)-EMR	Peru	2001	[88]
Lilongwe EMR	Malawi	2001	[89]
Comprehensive Resource Emergency Ware (CAREWare)	Uganda	2003	[88]
PEPFAR Project	Tanzania	2004	[90]
Hakeem National E-Health system	Jordan	2009	[91]

solely on an online access control system is not advised, especially in developing nations, as access to the server may be hampered by a variety of unfavorable circumstances, such as frequent power outages that render the server unavailable. Because of the inability to select an access control method, EHRs are no longer accessible. While other contexts are resource-constrained, it is difficult to develop a single EHR architecture and implementation that will meet the needs of all environments. Adaptability, complexity, cost, incentives and external policy, implementation climate, technological constraints, standards boundaries, attitudinal constraints - individual and organizational behaviors - are other hurdles to EHR deployment () [96], [97].

While the developing world still witnesses a poor uptake of EHRs, recent years have been characterized by numerous studies aimed at identifying the critical factors affecting the adoption of EHR in the healthcare system, particularly in developing countries. A study by [74] revealed that patients are generally more optimistic about using electronic health (e-health) services than doctors in developing countries. Several other studies [98], [99], [100], [101], [102] also indicated that doctors in these countries tend to be reluctant to adopt new technologies. Further noting that, doctors' negative attitudes toward the EHR system are a result of technology anxiety and inefficient doctor-patient communication. In [103], the authors argue that physicians are also concerned that the EHR system will disrupt workflow and change current work practices.

Moreover, healthcare facilities in low- and middle-income nations, like those in affluent ones, also generate terabytes of multimedia data on a monthly basis in the course of documenting patients' health status and the care delivery process [104]. However, lack of standard criteria for health information data, technological problems, system interoperability, a lack of readily available, well-trained clinician informatics teams to oversee the process, privacy and confidentiality concerns, a small pool of potential vendors in the market, and vendor churn are other obstacles to the adoption of EHR systems in developing nations [105]. Also, the attitude of the government and key policymakers contribute massively to the low adoption rate in this region.

While the issue of EHR adoption is minimal in the industrialized world, issues such as EHR interoperability with clinical processes persist. In an effort to better understand safety dangers associated with EHRs and potential interoperability issues with other health IT during the care process, [105] examined reports of patient safety events (PSEs) stored in a database comprising different provider organizations. In this study, the authors discovered that, of the 1.735 million PSE reports, 2625 were identified as being connected to health IT, and further research revealed that radiology, laboratory, and pharmacy systems interfaces accounted for the majority of EHR interoperability PSE reports (i.e., medication-related). The majority of interoperability concerns in these clinical domains were connected to obtaining information from other health IT systems rather than giving information to other systems.

B. ISSUES, CHALLENGES AND RECOMMENDATIONS

The main problems with the design and use of EHRs, according to the findings of this study, are the lack of a common and unifying architecture, the lack of concept extraction standards (like standard sense inventories), and the limited robust capacity of analytical engines. There is a big need for a unified architecture that will support standardized interfaces for connecting different analytical engines made by different groups, allowing them to work together both in terms of meaning and process. After the passage of the Health Information Technology for Economic and Clinical Health Act in 2009, the adoption of EHRs in the United States increased rapidly, with approximately 86% of office-based physicians and 96% of non-federal hospitals using an EHR system as of 2017 [106]. Other studies also shown that developed countries such as Canada, the United Kingdom, Australia, and Denmark have made strides in the design and implementation of EHR as part of their national e-health infrastructure, though they have also struggled in their EHR mandate due to user resistance to EHR support for clinical processes, provider burnout, decreased satisfaction [106], [107], [108], [109], and EHR interoperability with other e-health systems [105].

Based on the study's findings, the following recommendations are offered: Governments and other key policymakers in developing countries could increase EHR system adoption by making legislation and implementing social strategies to encourage physicians to use the EHR system and by providing technical competence and training to make EHR system use easier. Data security and privacy remain critical issues in e-health. In developed countries, like Europe, e-health is based on policies to protect the data of citizens who are patients. So that patients can trust the system, developing countries must also pass laws to protect personal information.

Several studies show that clinicians in developed countries are trained using innovative technologies like 3D simulations, virtual reality, and robotics. Information and communication technology (ICT) is also part of the curriculum for medical courses in these countries. Medical informatics, bioinformatics, computational biology, and health informatics are among the new courses that have begun. The availability of ICT skills among clinicians is likely to result in the acceptance and use of e-health in primary care. This is because clinicians who know how to use ICT can see how it can help them carry out and improve the different processes in which they are involved. So, to have a positive view of electronic medical records, a good knowledge of information communication technology is required.

Numerous concepts have been suggested to address clinician burnout and patient dissatisfaction. Epic Systems Inc. in Verona, Wisconsin, USA, for example, created the Inpatient Provider Efficiency Profile (IP PEP) tool to determine where inpatient EHR users spend the majority of their time. Other regions continue to have a high demand for solutions of this type, which can only be met through impactful research aimed at understanding the root cause and scope of the problem. It is worthwhile to examine the system's evolution trend when analyzing the prospects of EHR. At the moment, the primary function of EHR systems is to store patient data for use by healthcare providers while maintaining data integrity and confidentiality. To provide a benchmark against which current and future EHR systems can be measured, Navigli in [110] defined significantly improved health care through computer technological competences as the vision of future patient records and patient record systems.

C. EHR AND CLINICAL ABBREVIATION USE

The longstanding practice of using acronyms and abbreviations in medical documentation is deeply ingrained in medical practice, with even the most junior medical and nursing school graduates being very comfortable with their usage [65]. The number of healthcare professionals who use these medical acronyms, as well as their frequency of use, is unknown, but it is certain that the number is substantial. In any medical document or drug prescription at a healthcare facility, at least one abbreviation can be found on each page of the patient's medical record. However, the question of whether the usage of medical abbreviations is dangerous and how many patients have been harmed as a result remains a topic for further research.

In an attempt to unveil the extent of inappropriate use of medical abbreviation in medical records and their comprehension issues, Hamiel et al. in [111] utilized as a model, ophthalmology consults in a tertiary hospital. In this study, the authors first mapped out the frequency of general English abbreviation in the department's EHR. The study included most frequent English abbreviations in the design of their cross-sectional survey to assess the attitude of non-ophthalmologist physicians toward abbreviation use and comprehension. The authors reported that of 437 records screened and 235 responses gotten, only 42.5% got at least 10% of the abbreviations, and none of the respondents was able to get all abbreviation correctly as intended.

As reported in [65], misinterpretation of ambiguous medical abbreviations has resulted in consistent increase in reported errors, some of which have caused adverse events, received by the US Institute of Safe Medication Practices (ISMP). The Joint Commission has provided updated regulations and a brief list of harmful medical abbreviations and dose expressions that should never be used to ensure safe usage of medical abbreviations. However, despite numerous condemnations from prominent organizations, medical acronyms are still heavily utilized, especially with the adoption of EHRs. Medical abbreviations are almost always present in medical records or prescriptions, putting junior healthcare staff in a difficult position to decipher the drug orders without the presence of the healthcare provider who wrote the abbreviations. The other option is to refuse to carry out any order with confusing abbreviations, but this may risk the patient's health.

Researchers are now having to deal with this lingering problem for the electronic form of medical records created in EHR. Since automated sense resolution of medical acronyms in such systems is core to avoiding improper communication, different medical NLP approaches have been suggested to deal with this problem. However, due to the nature of the task, most of these approaches still have trouble understanding and interpreting ambiguous short word form. Moreover, EHRs make it hard to figure out what an acronym means because it lacks a comprehensive list of acronyms full meaning and their methods for resolving acronyms' intended full sense remain not particularly good. In summary, medical errors can come from a variety of sources, but since the adoption of EHR has gained momentum, EHR-related errors from clinical acronyms use have been on the rise.

IV. NLP IN CLINICAL NARRATIVES

With the help of machine learning (ML) and deep learning (DL) methods, artificial intelligence (AI) in healthcare is better than other technologies at gathering information, processing it, and giving a clear result. When AI is used in medicine, the main goal is to find out how prevention or treatment affects how well a patient does. Even though AI has been used to handle medical data, the implementation of Electronic Health Record (EHR) systems has increased the utilization of AI technologies in healthcare. Due to the wide use of EHRs, the healthcare community now has access to a lot of discharge summaries, laboratory reports, progress notes, and other types of information. These clinical notes, particularly progress notes, include the patient's most recent pertinent information. Even though the information is particularly important for describing a patient's medical situation, it is mostly written down as unstructured text using highly specialized clinical language [112] and sometimes, ambiguous acronyms. In Fig. 3, we provide a good example of the use of acronym MR in two clinical notes. In Note 1, the acronym stands for "mental retardation". Based on the context of this note, it is quite simple to interpret it incorrectly as "mitral regurgitation," which may prompt additional imaging tests and the postponement or avoidance of non-urgent interventions due to a higher risk of complications. In Note 2, MR is defined as "mitral regurgitation".

However, it is widely established that unstructured data contain pertinent, extensive, and nuanced information regarding the symptoms trajectory and treatment processes done by and upon patients [65], [113], [114], making the problem of automatically extracting accurate and precise information from narrative notes worthwhile to tackle [115]. A significant amount of structured content is affected by high-flown manipulations or interpretation errors, such as upcoding and misclassification, but narrative content is primarily used to facilitate practitioners' recollection and as a means of doctor-doctor communication across different work shifts [65], [113]. A special kind of AI approach called Natural language processing (NLP) or text mining techniques, are the foundation for the methods used to process the unstructured data found in EHRs. These techniques are also instrumental for extracting relevant information from unstructured EHR data, such as clinical narratives, and transforming it into a structured format that can be easily analyzed.

Studies have shown that doctors and nurses often use acronyms and abbreviations in their clinical notes, which can hide important information like diseases or procedures. This section will go over previous research on the disambiguation of acronyms and abbreviations in clinical notes with NLP. We conducted a search primarily on Google Scholar and the Scopus database using combination keywords such as Natural language processing, NLP, electronic health record, EHR, text mining, acronyms, abbreviations, word sense disambiguation, WSD, and clinical note in order to examine the application of NLP in medicine for acronyms and abbreviation disambiguation. Even though some earlier publications on the topic of NLP are used, we focused on articles published in the previous five years because NLP applied in medicine is a relatively new field. We concentrated on publications published in the most prestigious journals dealing with clinical informatics, such as JAMIA, Computer Methods and Programs in Biomedicine, Journal of Medical Internet Research, Journal of Biomedical Informatics, and International Journal of Medical Informatics. Our search also considered papers that appear in the proceedings of prestigious international conferences and workshops like ACL, EMNLP, BioNLP, NAACL etc.

A. MEDICAL ACRONYMS SENSE DISAMBIGUATION

Clinical narratives in patient Electronic Health Records (EHRs) are riddled with abbreviations [116]. Disambiguating these abbreviations is a critical first step in developing clinical decision support technologies that rely on narratives [117]. Disambiguation of clinical acronyms and abbreviations is a subset of Word Sense Disambiguation (WSD), which is the process of determining the sense of a word to be activated based on the context of usage [118]. Several studies in general English and other languages have proposed numerous distinct approaches to WSD. Among these approaches are supervised machine learning [119], [120], semi-supervised machine learning [121], unsupervised machine learning [122], [123], and knowledge-based [19]. Because of the inherent linguistic fundamentals, researchers have been able to apply similar methods to biomedical literature and clinical text [17].

For medical acronyms and abbreviations, a variety of WSD methods have been proposed, including traditional supervised machine learning-based approaches with optimized features [2], [124], vector space model-based approaches [125], [126], hyper-dimensional computing-based algorithms [25], semi-supervised approaches [127], and unsupervised approaches grounded on topic-modeling method [107]. While disambiguation approaches based on supervised learning methods have been proven to be more effective compared to those based on un- or semi-supervised and knowledge-based methods, they do have a limitation. They often require upfront human intervention to appropriately label the input and output data. However, labeling huge datasets is cost prohibitive and labor-intensive. Additionally, majority of early NLP techniques to clinical abbreviations disambiguation require training a separate classifier for each ambiguous term, which can be challenging, and particularly impractical [128]. To overcome various challenges in this task, numerous approaches have been suggested including those that leverage statistical power across all instances and scale efficiently with the size of the vocabulary. In this subsection, we summarize the most recent ML-based and neural-based NLP techniques for acronym disambiguation in EHR. We examined earlier works based on the techniques used to carry out a variety of automated sense resolution tasks, including the identification of acronyms, the development of sense inventories, and other significant topics.

1) MACHINE LEARNING-BASED METHODS

Abbreviation disambiguation is a difficult issue for computers but has been tackled by a number of different approaches over the past two decades. Most of these methods [117], [126], [129] are based on supervised algorithms, such as Support Vector Machines (SVMs), Naive Bayes, and Random Forest classifiers which are trained on the number of

Note 1
…72 year-old female with DM2 (type 2 Diabetes Mellitus), myocardial infraction requiring CABG (coronary artery bypass graft), asthma, MR, and gem cell tumour with metastases to left upper lobe...

Note 2
…He also underwent an echocardiogram which showed left ventricular systolic function which was normal. He had mild MR and mild TR. He had some early diastolic dysfunction as well as biatrial enlargement...

FIGURE 3. Illustration of ambiguous acronym occurrence in clinical narratives, where the acronym "MR" is used in Note 1 and 2, but with different intended full forms.

times different senses appear together in clinical abstracts with automatically tagged medical concepts. During this time, semi-supervised, unsupervised, word-embedding, and knowledge-based algorithms also gained traction. In general, these methods are called ''artificial intelligence-based,'' and the most successful ones in this group are those that use machine learning.

Machine-learning (ML) techniques concentrate on the use of data and algorithms to imitate how humans learn, and progressively enhance its accuracy and performance. Unlike algorithmic programing, this branch of AI enables computer systems to learn from data and improve its performance on a given task, without such knowledge being expressly programmed in its memory. Using statistical methods, ML algorithms are trained to make classifications or predictions, and to learn from crucial patterns and insight in data. Different from traditional statistical and knowledge-based approaches, where human intervention is required at every stage including when variables of interest are being selected as well as during the creation of model with capability to predict outcome [130], ML-based approaches are fully automated and requires no human intervention. Moreover, the output of statistical models is by and large falsely influenced by the variables selected to be included by the user, and it does not also enable performance optimization. The output of ML-based models, however, is free from all these restrictions.

To disambiguate abbreviations and determine their intended meaning, classical ML-based NLP approaches utilize the local context of the abbreviation with respect to the statement they appear. Over the last couple of years, several ML-based NLP approaches have been explored in various studies as a viable innovation for resolving ambiguous acronyms in medical reports. For instance, [127] in their attempt to show the suitability of semi-supervised approaches as a viable alternative to fully supervised machine learning methods employed the Reverse substitution (RS) method, which automatically generates training data by swapping out expansions for the corresponding abbreviations. In this study, a large hand-annotated medical record with instances of seventy-four (74) ambiguous abbreviations was used to test a number of semi-supervised classification algorithms. The authors pointed out that despite large discrepancies between training and test corpora, classifiers nevertheless manage to attain up to 90% accuracy. However, as shown by the fact that the dispersion of terms in their full and shortened forms are usually not the same, RS results in unbalanced training sets [131].

Using three techniques from their prior research —word sense disambiguation techniques for clinical abbreviations, clustering-based semi-automated methods to generate potential abbreviation senses, and machine learning-based algorithms to recognize abbreviations from a clinical corpus — [8] also created a system for medical acronyms detection and disambiguation (CARD). Using medical text data from the Vanderbilt University Medical Center (VUMC), the suggested methodology was utilized to build two detailed sense inventories for abbreviations in clinic visit notes and discharge summaries. By achieving an F1 score of 0.755 for detecting and resolving sense of all abbreviations in a corpus from the VUMC discharge summaries using the sense inventories generated from discharge summaries (cTAKES) [132], CARD outperformed the existing clinical NLP system (MetaMap) [133], [134].

In [135], the authors applied unsupervised approaches for expanding and disambiguating medical acronyms and abbreviations. To disambiguate multi-sense clinical acronyms, the authors combine statistical machine translation with document-context neural language models in this research. In addition, the study looks into the usage of mismatched training data and self-training. These algorithms are tested using nursing progress notes and achieve 71.6% disambiguation accuracy without the use of any manual annotation. In their research, [136] proposed investigating the impact of word-embedding on acronym disambiguation by offering two word-embedding models based on [137]. The model proposed in this paper was tested using ScienceWISE and MSH datasets. The paper's experimental results show that word-embedding has a considerable impact on the accuracy of acronym disambiguation without knowledge bases, and the results are also remarkably robust across datasets from diverse domains.

Nakayama et al., in [138] proposed using abbreviation normalization, lemmatization, and stop word removal to extract structured information from nursing notes. The authors created a pipeline that conducted straightforward abbreviation disambiguation, using popular preprocessing methods used in natural language processing, and then used sentiment analysis and dimensionality reduction based on topic modeling to create meaningful features from clinical notes. The study discovered that using abbreviation disambiguation in nursing notes for subsequent topic modeling and sentiment analysis enhanced prediction of in-hospital and 30-day mortality while controlling for comorbidities. In [139], Jaber and Martinez studied four approaches to trained two supervised machining learning methods with pre-trained word embeddings integrated within these pipelines as features. Their training features includes the context information of the target abbreviation and dataset used for training is small and obtained from a university-linked health care center. The two supervised ML algorithms are SVM and Naïve Bayes, with SVM showing the best performance in all the four studied approaches.

While ML algorithms have been shown in multiple studies to be successful in clinical acronym and abbreviation disambiguation, their practical deployment in clinical systems is currently limited. Furthermore, the lack of sufficient training data prevented further development and deployment of algorithms for automatic abbreviation disambiguation. Besides, these methods only utilized the local contextual information contained in the data for earning. However, recently evolving methods are now leveraging the contextualized embeddings obtained from deep learning models (such as BERT and ELMo model variants) to fine-tune abbreviation disambiguation models. In the subsection that follows, we provide a detailed review of some recent works that adopt this approach.

2) DEEP LEARNING-BASED METHODS

While machine learning is widely used in today's NLP, classical ML-based methods primarily involve optimizing weights for pre-designed representations and features created by humans. Deep learning (DL) is a subclass of ML whose objective is to explore how computers can leverage data to develop features and representations that are suitable for intricate interpretation tasks. Recent research has demonstrated that DL approaches are at the forefront of many NLP tasks [140], [141]. Despite several research demonstrating the appropriateness of DL-based techniques for biological and clinical data and possible applications, the use of deep learning approaches in medical text simplification has been gradual. There could be various explanations for this. While deep architectures can be significantly more efficient than other traditional algorithms at capturing fine intricacies in data structure, Deep neural networks (DNNs), particularly convolutional neural networks, are extremely complicated machines with hundreds of millions of weights, making them data hungry, and demanding huge, supervised data for training and regularization.

In recent years, several papers on the disambiguation of clinical acronyms have utilized the technique. The authors in [117] for instance, trained a Convolutional Neural Network (CNN) to differentiate between various acronyms senses. In this study, the authors utilized three datasets, the first two of which were 1,001 longitudinal patient records obtained from the Cleveland Clinic in Ohio (USA) and totaling 117,526 clinical notes. The first dataset was produced automatically using reversed substitution, the second dataset was manually annotated from set-aside notes, and the third dataset was produced by a team at the University of Minnesota [142] and made publicly available. It contains 37,500 occurrences of 75 abbreviations, with approximately 500 occurrences per abbreviation. Ultimately, they determined that the CNN model performed the best (with an accuracy of 1–4 points on all three datasets) compared to more conventional methods such as SVM.

Also, in [131], the authors proposed a method to enhance a model's generalizability via cutting-edge data augmentation strategies. The suggested techniques make use of relevant data from biomedical ontologies, including global context information and related medical concepts, within the medical note. The author trained the model on a public dataset (MIMIC III) and evaluated its performance on automatically generated and manually annotated datasets from various sources (MIMIC III, CASI, i2b2). Together, these techniques improve abbreviation disambiguation accuracy by up to 17% on hand-labeled data without sacrificing performance on a MIMIC III held-out test set.

While differentiating between abbreviation disambiguation and abbreviation expansion, Kim et al., [143] noted that expansion is much easier as compared to disambiguation of abbreviation. In this paper, the authors examined two approaches, namely non-sense-based and sense-based approaches to abbreviation expansion. The former utilizes state-of-the-art language models alongside unstructured information contained in clinical notes, exclusively on a lexical level. On the other hand, the latter considered the two tasks of abbreviation expansion and disambiguation, while integrating sense information alongside the unstructured data for language model training. Particularly, the language models considered in this work are the masked BERT [144] language model and the second is novel adaptation of the XLNet language model [145] called length-agnostic permutation XLNet. The findings of this research support the notion that expanding abbreviations might be less challenging than disambiguating them, since the non-sense-based methods perform better than the sense-based methods.

To improve the accuracy of abbreviation disambiguation in biomedicine, the authors in [146] proposed a disambiguation pipeline based on graph attention neural network. The semantic class, part of speech, as well as the words in context of the ambiguous acronyms are taking as the input to the proposed model, while constructing the graph with the sentence and features of disambiguation as nodes. To dynamically modify the edge weight between two adjacent nodes, the author applied a multi-head graph attention mechanism. In this study, the author considered 28 ambiguous biomedical vocabularies from MSH dataset. However, the approach followed by authors is that of the early work in clinical abbreviation disambiguation where separate classifiers are trained for each ambiguous word.

Jaber and Martínez in [147] explore the deep contextualized representations from large language model like BERT for disambiguating clinical abbreviation. This work investigates a series of fine-turning approaches on clinical abbreviation disambiguation by performing various experiments with different pretrained clinical BERT. The utilization of deep contextualized representations from Bioclinical, BlueBERT, and MS_BERT pretrained models in one-fits-all classifiers led to enhanced accuracy on the University of Minnesota (UMN) dataset. Specifically, the Bioclinical, BlueBERT, and MS_BERT models attained accuracy rates of 98.99%, 98.75%, and 99.13%, respectively.

The authors in reference [7] utilize deep learning models trained on public web data to decipher abbreviations and shorthand in clinical text by substituting abbreviations with their corresponding meanings. The type of models utilized in this study are Text-to-Text Transfer Transformers (T5), specifically, designed as encoder-decoder architectures. The result reported in this work uses the T5 80B variation. Furthermore, the authors experimented with three other variants of T5 models, with all been pretrained on web corpus using the MLM (Masked Language Modeling) loss function. These models include T5 11B, T5 large, with 770 million parameters, and T5 small with 60 million parameters. The study introduces a novel translation model capable of detecting and expanding numerous abbreviations in real clinical notes with exceptional accuracy. The model achieves accuracies ranging from 92.1% to 97.1% on multiple external test datasets, outperforming board-certified physicians with a total accuracy of 97.6% compared to 88.7%.

The authors in [148] suggested a few-shot learning strategy to make the most out of the limited annotated data currently available for clinical abbreviation disambiguation. To acquire better contextualized sentence representations for clinical abbreviation disambiguation, a neural network based on topic-attention was specifically used. Their model is tested on a manually built balanced dataset after being trained on a training set that includes 30 abbreviation words taken from a publicly available dataset of clinical domain acronyms and abbreviations. The author demonstrates that adding subject information to the sentence representation significantly improves effectiveness on small-scale uneven training datasets as compared to many baseline models.

The base model's average AUC is 0.7189, whereas the topic-attention model (ELMo+Topic) suggested in this study obtains an average AUC of 0.8196. The fact that it is expensive and time-consuming to create hand-labeled medical abbreviation datasets for training and testing DNN models, coupled with the fact that there are only a few Clinical Abbreviation datasets containing training data and labels available, research employing deep learning-based method are limited. Moreover, only limited research attention has been given to the issue of data sparsity over the years. To address this issue, which has been one of the most significant barriers preventing the use of many current NLP methods in clinical settings, [149] present MeDAL, a sizable medical text dataset annotated for abbreviation disambiguation, developed for natural language understanding pre-training in the medical domain. The authors utilized this dataset to pre-train several deep learning-based models of common architectures, including LSTM, LSTM+attention and ELECTRA, while conclusively demonstrating that such pre-training improves performance and computational efficiency when fine-tuning on subsequent medical tasks.

Overall, recent advances in deep learning techniques have been greatly outperforming classical statistical and knowledge-based algorithms, particularly in healthcare application, due to their ability to process and analyse vast amounts of complex medical data more accurately and efficiently. These improvements can be summarised as follows:

1. Large and Complex Data Handling capability: Deep learning algorithms are capable of processing larger and more complex datasets compared to traditional machine learning methods. This is because deep learning models use multiple layers of artificial neural networks to extract features and learn complex patterns in the data.
2. Data Integration: Deep learning techniques can be used to integrate data from multiple sources, such as EHRs, genomics, and social determinants of health, to provide a more comprehensive view of patient health. This can help healthcare providers make more informed decisions about patient care.
3. Automated Feature Engineering: Deep learning methods can automatically extract relevant features from data, eliminating the need for manual feature engineering in traditional machine learning. This is especially useful when dealing with large and complex datasets where manual feature engineering is time-consuming and error prone.
4. Non-Linear Relationships: Deep learning algorithms can model non-linear relationships between inputs and outputs, which traditional machine learning methods cannot easily capture. This is useful in tasks like image and speech recognition, where the relationships between inputs and outputs can be highly complex.
5. Transfer Learning: Deep learning models can be trained on large datasets and then fine-tuned on smaller datasets for specific tasks. This transfer learning approach can save time and resources, as it avoids the need to train deep learning models from scratch.
6. Scalability: Deep learning algorithms can be easily scaled to handle large datasets and compute-intensive tasks by leveraging distributed computing platforms and graphics processing units (GPUs). This makes it possible to process massive amounts of data in a reasonable amount of time.
7. Enhanced Accuracy: One of the main advantages of deep learning techniques is their ability to improve accuracy. Neural networks can learn from vast amounts of data and recognize complex patterns in the data that may be

difficult for classical statistical or knowledge-based algorithms to identify.

In summary, the use of deep learning techniques in healthcare has shown great promise in improving patient outcomes and reducing healthcare costs. As these technologies continue to develop and become more widely adopted, we can expect to see even more significant advancements in healthcare.

V. DISCUSSION

Patient safety is a critical healthcare problem due to the consequences of iatrogenic injuries. Medication errors in critical care are frequent, dangerous, and preventable. Although the primary objective for adopting the EHR system was to resolve some problems bedeviling medical healthcare delivery, its adoption has led to an increase in medical errors. The use of acronyms increased as a result of the transition from traditional paper-based records to electronic health records, many of which are notorious for being ambiguous. However, human factor research carried out in non-medical situations suggests that requiring higher vigilance from medical practitioners may not lead to a meaningful improvement in safety. Finding issues and redesigning defective systems appears to be a more effective way to reduce human error.

As a remedy, NLP has been adopted as a viable solution to disambiguate medical acronyms and abbreviations in clinical notes. Models built using sophistical NLP algorithms are usually integrated into an EHR system, and often function both as an auto-completion tool during medical report writing as well as intended full meaning suggester during information retrieval. The model, however, performs these functions while taking cognizant of the context of the acronym's usage in the report statement. Over the years, several approaches have been proposed. Notably, artificial intelligence-based solutions have been generally recognized as the best solution for seeking a complete form to acronyms in medical note. Existing AI methods applied over the years include knowledge-based methods, statistical approach, and machine learning based techniques. Recent approaches to Natural Language Processing (NLP) based on neural networks and deep learning, on the other hand, have achieved substantial advances, surpassing conventional statistical as well as knowledge-based methods on a number of tasks. A noteworthy limitation observed in most of the existing literature is that datasets of only hundreds or thousands of documents are used to train machine learning models.

Another issue that marred the use of this technology in healthcare is ethical concerns. This is related to the potential for bias in the algorithms used in NLP and deep learning techniques. If the algorithms are not designed and trained appropriately, they may produce biased results that could negatively impact certain patient populations, such as those with specific health conditions or demographic characteristics. This could result in discriminatory treatment or exacerbate existing health disparities. Additionally, there are concerns about the accountability and transparency of NLP and deep learning algorithms. Healthcare providers must be able to explain how these algorithms make decisions and ensure that the decisions are fair and justifiable. Patients and other stakeholders should also be able to understand and question the decisions made by these algorithms.

Furthermore, the use of NLP and deep learning techniques in healthcare could also raise issues related to informed consent. Patients may not fully understand the implications of allowing their data to be used in research and may not be aware of the potential risks and benefits of these techniques. Healthcare providers must ensure that patients are fully informed and provide clear and transparent consent processes. In conclusion, the use of NLP and deep learning techniques in healthcare has significant potential to improve patient care and health outcomes. However, ethical considerations related to patient privacy, bias, accountability, and informed consent must be addressed to ensure that these techniques are used in an ethical and responsible manner. More details on other constraints and suggested recommendations are provided in the subsection that follows.

A. DIFFICULTIES AND CHALLENGES

1. **Scarcity of labeled training data**. Modern machine learning (ML) techniques, particularly deep learning approaches, are highly promising for automating a range of clinical and research frameworks, but they require a significant amount of annotated data for training. Due to the cognitive difficulty of abbreviation disambiguation task and the considerable variation in the quality of the data, annotating EHR data can be costly and difficult [131], [150]. Unfortunately, there are frequently insufficient amounts of useful EHR data, and since neural networks need a lot of text to train on, this is a problem. Additionally, for certain tasks, only certified annotators may be qualified to perform annotations, further adding to the cost and difficulty of the process. Ensuring annotation quality can also be challenging as annotators may have disagreements, especially when dealing with domain-specific long forms or concepts of abbreviations. Furthermore, a significant portion of publicly available annotated data in this field is in English, which presents additional challenges for research in other languages. The sparse and imbalanced nature of datasets in this particular domain has several consequences. One of the main consequences is that it restricts the development and deployment of methods for automated abbreviation disambiguation. Due to the limited availability of data, methods built solely on these datasets are susceptible to overfitting and may not be applicable to abbreviations that are not present in the training data.
2. **Imbalance data.** A common challenge faced in real-world datasets, such as clinical notes, is the presence of imbalanced class distributions. This means that some classes are more prevalent than others, resulting in insufficient training input for traditional classifiers. The uneven distribution of data presents challenges in creating

precise automated abbreviation disambiguation systems. It becomes particularly difficult to train a model that can accurately predict the full form of an abbreviation when there is limited data available for learning. This issue arises from the imbalance in class distribution within publicly available datasets, which can result in overfitting and render existing methods ineffective for abbreviations not included in the training data.

3. **Privacy.** Because of the highly sensitive nature of the information contained in EHRs, as well as the existence of regulatory laws such as the (US) Health Insurance Portability and Accountability Act (HIPAA), maintaining privacy within analytic pipelines is critical [151], [152]. As a result, additional privacy-protecting steps are frequently required before any downstream tasks or data can be shared with others. It is an expensive process to remove personal information from a large corpus of EHRs [150]. It is difficult to automate and requires domain experts as annotators.
4. **Explainability and interpretabilit**y. The issue of deep learning explainability and interpretability is not peculiar to application in healthcare alone, it is a common problem that is still being instigated in general deep learning research. When compared to other techniques, deep neural networks can produce better results. However, they are frequently regarded as ''black boxes'' in many disciplines [153], [154]. A neural network model typically has a large number of trainable parameters, which makes it extremely difficult to interpret the model. Moreover, neural networks have complex architectures and non-linear layers making them more difficult to interpret than linear models, which are typically simpler and easier to understand. To increase model transparency, a few efforts have recently been made to create explainable deep neural networks [155], [156], [157], [158].

B. FUTURE RESEARCH DIRECTION

The fundamental cause of poor data use for training of supervised ML/DL models for disambiguation is annotation difficulties observed by supervised machine learning algorithms. However, the use of more contemporary deep learning methods has been hampered by the necessity to generate a large, labeled corpus. Among the potential prospects for this area of research is the use of generative models to generate medical acronyms and corresponding possible senses that may be used to train a machine learning model. Also, while methods such as pattern matching, language modeling, and machine learning have produced promising results in the disambiguation of acronyms, there is need to explore the potentials of deep learning-based methods, especially those based on the most recent powerful natural language models such as GPT-3, BERT, diffusion models etc.

In addition, to encourage the development of transparent DL models for healthcare applications, future research should focus on the development and training of explainable and interpretable deep learning models. Such models should scale beyond the current models with only static knowledge distillation, while incorporating dynamism. Also unsupervised learning is a promising research direction in deep learning, as it can help to overcome some of the limitations of supervised learning, such as the need for labeled data, and can enable more autonomous and adaptive learning systems.

VI. CONCLUSION

Electronic health records (EHRs), which are computerized compilations of patient healthcare events and observations, are widely utilized in the medical field and are indispensable for healthcare delivery, operations, and research. Clinical narratives in patient Electronic Health Records (EHRs) are notoriously difficult to automate due to the prevalence of abbreviations [116]. The majority of the information stored in EHRs consists of unstructured text (e.g., doctor notes, surgical summaries), which is typically underutilized for secondary purposes. Recent advances in NLP neural networks and deep learning techniques have surpassed classical statistical and knowledge-based algorithms in a number of tasks. This article provides a comprehensive overview on medical error, EHR and its adoption in both developed and developing nations. We also discussed EHR-related error from acronyms and abbreviation usage, while summarizing current ML- and DL-based NLP approaches for abbreviation disambiguation in clinical setting. This paper adopted a comprehensive approach to carefully review EHR-related medical errors caused by clinicians' interactions with the EHR systems. These errors could appear during the data entry process and/or during subsequent information retrieval, and it is possible that automated WSD could be used as an effective remedy. A detailed overview was presented on medical error, its causes, and unintended repercussions. We also discussed EHR-related errors as a subset in the general medical error. We examined EHR adoption issues and challenges in both developed and developing countries, while suggesting appropriate solutions. To sum up, we critically analyzed the research trend and future direction in AI and NLP for medical acronyms sense resolution in clinical note.

This survey found that despite the widespread success of deep learning techniques in the general NLP domain, it remains challenging to apply them in the healthcare system owing to the scarcity as well as complexity of obtaining domain-specific text data and the ongoing evolution of research seeking the interpretability and explainability of deep learning techniques. In terms of decision-making and interpretability, better knowledge and information extraction from unstructured data and practical merging of both structured and unstructured data are prospective directions for this field's future development. To atone for the lack of labeled textual data, another approach for EHR tasks could be unsupervised learning or adoption of pre-trained models, which can be fine-tuned with the limited data available via transfer learning. This study is intended to inspire readers and advance future NLP developments or clinical domain acronym disambiguation.

Despite the widespread success of DL-based techniques in the general NLP domain, this survey found that applying them in the healthcare system remains difficult due to the scarcity and complexity of obtaining domain-specific textual data, as well as the ongoing evolution of research seeking the interpretability and explainability of deep learning techniques. Better knowledge and information extraction from unstructured data, as well as practical merging of both structured and unstructured data, are prospective directions for this field's future development in terms of decision-making and interpretability.

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REFERENCES

[1] S. Moon, "Automatic word sense disambiguation of acronyms and abbreviations in clinical texts," Fac. Graduate School, Univ. Minnesota, Minneapolis, MN, USA, Tech. Rep. 3549247, 2012.

[2] S. Moon, S. Pakhomov, N. Liu, J. O. Ryan, and G. B. Melton, "A sense inventory for clinical abbreviations and acronyms created using clinical notes and medical dictionary resources," *J. Amer. Med. Inform. Assoc.*, vol. 21, no. 2, pp. 299–307, Mar. 2014.

[3] D. R. Hunt et al., "Fundamentals of medicare patient safety surveillance: Intent, relevance, and transparency," in *Advances in Patient Safety: From Research to Implementation* (Concepts and Methodology), vol. 2. Rockville, MD, USA: Agency for Healthcare Research and Quality (US), 2005.

[4] I. F. Kuhn, "Abbreviations and acronyms in healthcare: When shorter isn't sweeter," *Pediatric Nursing*, vol. 33, no. 5, pp. 392–398, 2007.

[5] K. E. Walsh and J. H. Gurwitz, "Medical abbreviations: Writing little and communicating less," *Arch. Disease Childhood*, vol. 93, no. 10, pp. 816–817, Oct. 2008.

[6] M. Chemali, E. J. Hibbert, and A. Sheen, "General practitioner understanding of abbreviations used in hospital discharge letters," *Med. J. Aust.*, vol. 203, no. 3, p. 147, Aug. 2015.

[7] A. Rajkomar, E. Loreaux, Y. Liu, J. Kemp, B. Li, M.-J. Chen, Y. Zhang, A. Mohiuddin, and J. Gottweis, "Deciphering clinical abbreviations with a privacy protecting machine learning system," *Nature Commun.*, vol. 13, no. 1, p. 7456, Dec. 2022.

[8] Y. Wu, J. C. Denny, S. T. Rosenbloom, R. A. Miller, D. A. Giuse, L. Wang, C. Blanquicett, E. Soysal, J. Xu, and H. Xu, "A long journey to short abbreviations: Developing an open-source framework for clinical abbreviation recognition and disambiguation (CARD)," *J. Amer. Med. Inform. Assoc.*, vol. 24, no. e1, pp. e79–e86, Apr. 2017.

[9] M. Junaid, S. Ali, F. Eid, S. El-Sappagh, and T. Abuhmed, "Explainable machine learning models based on multimodal time-series data for the early detection of Parkinson's disease," *Comput. Methods Programs Biomed.*, vol. 234, Jun. 2023, Art. no. 107495.

[10] S. El-Sappagh, H. Saleh, F. Ali, E. Amer, and T. Abuhmed, "Two-stage deep learning model for Alzheimer's disease detection and prediction of the mild cognitive impairment time," *Neural Comput. Appl.*, vol. 34, no. 17, pp. 14487–14509, Sep. 2022.

[11] F. Juraev, S. El-Sappagh, E. Abdukhamidov, F. Ali, and T. Abuhmed, "Multilayer dynamic ensemble model for intensive care unit mortality prediction of neonate patients," *J. Biomed. Informat.*, vol. 135, Nov. 2022, Art. no. 104216.

[12] O.-P. Rinta-Koski, S. Särkkä, J. Hollmén, M. Leskinen, and S. Andersson, "Gaussian process classification for prediction of in-hospital mortality among preterm infants," *Neurocomputing*, vol. 298, pp. 134–141, Jul. 2018.

[13] M. C. Data and R. Pirracchio, "Mortality prediction in the ICU based on MIMIC-II results from the super ICU learner algorithm (SICULA) project," in *Secondary Analysis of Electronic Health Records*. Cham, Switzerland: Springer, 2016, pp. 295–313.

[14] F. Ali, S. El-Sappagh, S. M. R. Islam, A. Ali, M. Attique, M. Imran, and K.-S. Kwak, "An intelligent healthcare monitoring framework using wearable sensors and social networking data," *Future Gener. Comput. Syst.*, vol. 114, pp. 23–43, Jan. 2021.

[15] F. Ali, S. El-Sappagh, S. M. R. Islam, D. Kwak, A. Ali, M. Imran, and K.-S. Kwak, "A smart healthcare monitoring system for heart disease prediction based on ensemble deep learning and feature fusion," *Inf. Fusion*, vol. 63, pp. 208–222, Nov. 2020.

[16] G. Manogaran, R. Varatharajan, D. Lopez, P. M. Kumar, R. Sundarasekar, and C. Thota, "A new architecture of Internet of Things and big data ecosystem for secured smart healthcare monitoring and alerting system," *Future Gener. Comput. Syst.*, vol. 82, pp. 375–387, May 2018.

[17] M. J. Schuemie, J. A. Kors, and B. Mons, "Word sense disambiguation in the biomedical domain: An overview," *J. Comput. Biol.*, vol. 12, no. 5, pp. 554–565, Jun. 2005.

[18] H. Xu, M. Markatou, R. Dimova, H. Liu, and C. Friedman, "Machine learning and word sense disambiguation in the biomedical domain: Design and evaluation issues," *BMC Bioinf.*, vol. 7, no. 1, pp. 1–16, Dec. 2006.

[19] M. Joshi, S. Pakhomov, T. Pedersen, and C. G. Chute, "A comparative study of supervised learning as applied to acronym expansion in clinical reports," in *Proc. AMIA Annu. Symp.* Bethesda, MD, USA: American Medical Informatics Association, 2006, p. 399.

[20] G. K. Savova, A. R. Coden, I. L. Sominsky, R. Johnson, P. V. Ogren, P. C. D. Groen, and C. G. Chute, "Word sense disambiguation across two domains: Biomedical literature and clinical notes," *J. Biomed. Informat.*, vol. 41, no. 6, pp. 1088–1100, Dec. 2008.

[21] A. J. Jimeno-Yepes and A. R. Aronson, "Knowledge-based biomedical word sense disambiguation: Comparison of approaches," *BMC Bioinf.*, vol. 11, no. 1, pp. 1–12, Dec. 2010.

[22] B. T. McInnes and M. Stevenson, "Determining the difficulty of word sense disambiguation," *J. Biomed. Informat.*, vol. 47, pp. 83–90, Feb. 2014.

[23] I. Spasic and G. Nenadic, "Clinical text data in machine learning: Systematic review," *JMIR Med. Informat.*, vol. 8, no. 3, Mar. 2020, Art. no. e17984.

[24] T. L. Rodziewicz, B. Houseman, and J. E. Hipskind, "Medical error reduction and prevention," in *StatPearls*. Treasure Island, FL, USA: StatPearls Publishing, 2022.

[25] A. Bari, R. A. Khan, and A. W. Rathore, "Medical errors; causes, consequences, emotional response and resulting behavioral change," *Pakistan J. Med. Sci.*, vol. 32, no. 3, p. 523, May 2016.

[26] J. A. Harolds, "Quality and safety in health care. Part III: To err is human," *Clin. Nucl. Med.*, vol. 40, no. 10, pp. 793–795, 2015.

[27] P. Aspden and P. Aspden, *Preventing Medication Errors*. Washington, DC, USA: National Academies Press, 2007.

[28] A. K. Jha, I. Larizgoitia, C. Audera-Lopez, N. Prasopa-Plaizier, H. Waters, and D. W. Bates, "The global burden of unsafe medical care: Analytic modelling of observational studies," *BMJ Qual. Saf.*, vol. 22, no. 10, pp. 809–815, Oct. 2013.

[29] M. Panagioti, K. Khan, R. N. Keers, A. Abuzour, D. Phipps, E. Kontopantelis, P. Bower, S. Campbell, R. Haneef, A. J. Avery, and D. M. Ashcroft, "Prevalence, severity, and nature of preventable patient harm across medical care settings: Systematic review and meta-analysis," *BMJ*, vol. 366, p. l4185, Jul. 2019.

[30] E. N. de Vries, M. A. Ramrattan, S. M. Smorenburg, D. J. Gouma, and M. A. Boermeester, "The incidence and nature of in-hospital adverse events: A systematic review," *Qual. Saf. Health Care*, vol. 17, no. 3, pp. 216–223, Jun. 2008.

[31] *Conceptual Framework for the International Classification for Patient Safety Version 1.1: Final Technical Report January 2009*, WHOP Safety, World Health Org., Geneva, Switzerland, 2010.

[32] M. A. Makary and M. Daniel, "Medical error—The third leading cause of death in the U.S.," *BMJ*, vol. 353, May 2016, Art. no. i2139.

[33] B. Shelley, "'Primum non nocere' harmful medical mistakes, hubris syndrome, and human fallibility; getting to the heart of the matter," *Arch. Med. Health Sci.*, vol. 6, no. 2, p. 195, 2018.

[34] R. L. Wears and L. L. Leape, "Human error in emergency medicine," *Ann. Emergency Med.*, vol. 34, no. 3, pp. 370–372, Sep. 1999.

[35] L. L. Leape, "Error in medicine," *J. Amer. Med. Assoc.*, vol. 272, no. 23, pp. 1851–1857, Dec. 1994.

[36] J. E. Gracia, R. B. Serrano, and J. F. Garrido, "Medication errors and drug knowledge gaps among critical-care nurses: A mixed multi-method study," *BMC Health Services Res.*, vol. 19, no. 1, pp. 1–9, Dec. 2019.

[37] D. Kopec, M. Kabir, D. Reinharth, O. Rothschild, and J. Castiglione, "Human errors in medical practice: Systematic classification and reduction with automated information systems," *J. Med. Syst.*, vol. 27, pp. 297–313, Aug. 2003.
[38] N. Alrabadi, S. Shawagfeh, R. Haddad, T. Mukattash, S. Abuhammad, D. Al-Rabadi, R. A. Farha, S. AlRabadi, and I. Al-Faouri, "Medication errors: A focus on nursing practice," *J. Pharmaceutical Health Services Res.*, vol. 12, no. 1, pp. 78–86, 2021.
[39] J. J. Robertson and B. Long, "Suffering in silence: Medical error and its impact on health care providers," *J. Emergency Med.*, vol. 54, no. 4, pp. 402–409, Apr. 2018.
[40] O. Ozeke, V. Ozeke, O. Coskun, and I. I. Budakoglu, "Second victims in health care: Current perspectives," in *Advances in Medical Education and Practice*. Taylor & Francis: Taylor & Francis, 2019, pp. 593–603.
[41] S. M. Dovey, R. L. Phillips, L. A. Green, and G. E. Fryer, "Types of medical errors commonly reported by family physicians," *Amer. Family Physician*, vol. 67, no. 4, p. 697, 2003.
[42] S. Kuitunen, I. Niittynen, M. Airaksinen, and A.-R. Holmström, "Systemic causes of in-hospital intravenous medication errors: A systematic review," *J. Patient Saf.*, vol. 17, no. 8, pp. e1660–e1668, 2021.
[43] R. J. Desai, C. E. Williams, S. B. Greene, S. Pierson, A. J. Caprio, and R. A. Hansen, "Analgesic medication errors in North Carolina nursing homes," *J. Pain Palliative Care Pharmacotherapy*, vol. 27, no. 2, pp. 125–131, Jun. 2013.
[44] E. A. C. Gorgich, S. Barfroshan, G. Ghoreishi, and M. Yaghoobi, "Investigating the causes of medication errors and strategies to prevention of them from nurses and nursing student viewpoint," *Global J. Health Sci.*, vol. 8, no. 8, p. 220, Dec. 2015.
[45] K. A. Kowalczyk and A. Majewski, "Analysis of surgical errors associated with anatomical variations clinically relevant in general surgery. Review of the literature," *Transl. Res. Anatomy*, vol. 23, Jun. 2021, Art. no. 100107.
[46] P. Fekri, J. Dargahi, and M. Zadeh, "Deep learning-based haptic guidance for surgical skills transfer," *Frontiers Robot. AI*, vol. 7, Jan. 2021, Art. no. 586707.
[47] M. S. Sheikh, G. Nelson, S. L. Wood, and A. Metcalfe, "Surgical errors and complications following cesarean delivery in the United States," *Amer. J. Obstetrics Gynecol. MFM*, vol. 2, no. 1, Feb. 2020, Art. no. 100071.
[48] J. E. Berner and E. Ewertz, "The importance of non-technical skills in modern surgical practice," *Cirugía Española, English Ed.*, vol. 97, no. 4, pp. 190–195, Apr. 2019.
[49] M. Jukić, I. Biuk, and Z. Pogorelić, "The incidence and causes of unplanned reoperations as a quality indicator in pediatric surgery," *Children*, vol. 9, no. 1, p. 106, Jan. 2022.
[50] F. von Bechtolsheim, S. Schmidt, S. Abel, A. Schneider, M. Wekenborg, S. Bodenstedt, S. Speidel, J. Weitz, F. Oehme, and M. Distler, "Does speed equal quality? Time pressure impairs minimally invasive surgical skills in a prospective crossover trial," *Int. J. Surgery*, vol. 104, Aug. 2022, Art. no. 106813.
[51] T. N. Cohen, B. L. Gewertz, and D. Shouhed, "A human factors approach to surgical patient safety," *Surgical Clinics North Amer.*, vol. 101, no. 1, pp. 1–13, Feb. 2021.
[52] A. Ammar, "Neurosurgeon is the second victim of surgical adverse events and errors: A road map for mitigation and learning opportunity," in *Learning and Career Development in Neurosurgery: Values-Based Medical Education*. Cham, Switzerland: Springer, 2022, pp. 199–211.
[53] M. Plebani and G. Lippi, "Improving diagnosis and reducing diagnostic errors: The next frontier of laboratory medicine," *Clin. Chem. Lab. Med.*, vol. 54, no. 7, pp. 1117–1118, Jul. 2016.
[54] J. Hickner, D. G. Graham, N. C. Elder, E. Brandt, C. B. Emsermann, S. Dovey, and R. Phillips, "Testing process errors and their harms and consequences reported from family medicine practices: A study of the American academy of family physicians national research network," *Qual. Saf. Health Care*, vol. 17, no. 3, pp. 194–200, Jun. 2008.
[55] T. K. Gandhi, A. Kachalia, E. J. Thomas, A. L. Puopolo, C. Yoon, T. A. Brennan, and D. M. Studdert, "Missed and delayed diagnoses in the ambulatory setting: A study of closed malpractice claims," *Ann. Internal Med.*, vol. 145, no. 7, pp. 488–496, 2006.
[56] T. L. Wahls and P. M. Cram, "The frequency of missed test results and associated treatment delays in a highly computerized health system," *BMC Family Pract.*, vol. 8, no. 1, pp. 1–8, Dec. 2007.
[57] A. Kachalia, T. K. Gandhi, A. L. Puopolo, C. Yoon, E. J. Thomas, R. Griffey, T. A. Brennan, and D. M. Studdert, "Missed and delayed diagnoses in the emergency department: A study of closed malpractice claims from 4 liability insurers," *Ann. Emergency Med.*, vol. 49, no. 2, pp. 196–205, Feb. 2007.
[58] G. Sezgin, L. Li, J. Westbrook, E. Wearne, D. Azar, A. McLeod, C. Pearce, V. Ignjatovic, P. Monagle, and A. Georgiou, "Influence of serum iron test results on the diagnosis of iron deficiency in children: A retrospective observational study," *BMJ Open*, vol. 11, no. 7, Jul. 2021, Art. no. e046865.
[59] M. Plebani, "Diagnostic errors and laboratory medicine—Causes and strategies," *EJIFCC*, vol. 26, no. 1, pp. 7–14, 2015.
[60] S. Willis, A. Slattery, W. King, and K. Benner, "Therapeutic error calls among older adults reported to a regional poison control center in Alabama," *Southern Med. J.*, vol. 109, no. 6, pp. 356–362, Jun. 2016.
[61] A. Schicchi, G. Scaravaggi, V. M. Petrolini, A. Malovini, D. Lonati, M. Crevani, E. Buscaglia, and C. A. Locatelli, "Poisoning related to therapeutic error in prolonged low-dose methotrexate treatment," *Brit. J. Clin. Pharmacol.*, vol. 87, no. 5, pp. 2385–2391, May 2021.
[62] A. Rešić and N. Benco, "Intravenous acetaminophen overdose: A case report of a therapeutic error," *Arhiv Za Higijenu Rada i Toksikologiju*, vol. 72, p. 37, 2021.
[63] J. B. Leonard and W. Klein-Schwartz, "The others: Characterizing 'other' therapeutic errors reported to a poison center," *Clin. Toxicol.*, vol. 57, no. 7, pp. 652–656, Jul. 2019.
[64] J. Farokhzadian, A. Sabzi, and N. D. Nayeri, "Outcomes of effective integration of clinical risk management into health care from nurses' viewpoints: A qualitative study," *Int. Quart. Community Health Educ.*, vol. 41, no. 2, pp. 189–197, Jan. 2021.
[65] R. A. Tariq and S. Sharma, "Inappropriate medical abbreviations," in *StatPearls [Internet]*. Treasure Island, FL, USA: StatPearls Publishing, 2018.
[66] J. S. Ash, M. Berg, and E. Coiera, "Some unintended consequences of information technology in health care: The nature of patient care information system-related errors," *J. Amer. Med. Inform. Assoc.*, vol. 11, no. 2, pp. 104–112, Nov. 2003.
[67] A. J. Moy, J. M. Schwartz, R. Chen, S. Sadri, E. Lucas, K. D. Cato, and S. C. Rossetti, "Measurement of clinical documentation burden among physicians and nurses using electronic health records: A scoping review," *J. Amer. Med. Inform. Assoc.*, vol. 28, no. 5, pp. 998–1008, Apr. 2021.
[68] D. F. Sittig and H. Singh, "Legal, ethical, and financial dilemmas in electronic health record adoption and use," *Pediatrics*, vol. 127, no. 4, pp. e1042–e1047, Apr. 2011.
[69] D. W. Meeks, M. W. Smith, L. Taylor, D. F. Sittig, J. M. Scott, and H. Singh, "An analysis of electronic health record-related patient safety concerns," *J. Amer. Med. Inform. Assoc.*, vol. 21, no. 6, pp. 1053–1059, Nov. 2014.
[70] S. Palojoki, M. Mäkelä, L. Lehtonen, and K. Saranto, "An analysis of electronic health record–related patient safety incidents," *Health Informat. J.*, vol. 23, no. 2, pp. 134–145, Jun. 2017.
[71] S. Palojoki, K. Saranto, E. Reponen, N. Skants, A. Vakkuri, and R. Vuokko, "Classification of electronic health record–related patient safety incidents: Development and validation study," *JMIR Med. Informat.*, vol. 9, no. 8, 2021, Art. no. e30470.
[72] C. R. Denham, D. C. Classen, S. J. Swenson, M. J. Henderson, T. Zeltner, and D. W. Bates, "Safe use of electronic health records and health information technology systems," *J. Patient Saf.*, vol. 9, no. 4, pp. 177–189, 2013.
[73] M. Ghazisaeedi, N. Mohammadzadeh, and R. Safdari, "Electronic health record (EHR) as a vehicle for successful health care best practice," *Med. Arch.*, vol. 68, no. 6, p. 419, 2014.
[74] A. Hossain, R. Quaresma, and H. Rahman, "Investigating factors influencing the physicians' adoption of electronic health record (EHR) in healthcare system of Bangladesh: An empirical study," *Int. J. Inf. Manage.*, vol. 44, pp. 76–87, Feb. 2019.
[75] L. Schöpe and P. Knaup, "Using data from ambient assisted living and smart homes in electronic health records," *Methods Inf. Med.*, vol. 53, no. 3, pp. 149–151, 2014.
[76] E. L. Palmer, J. Higgins, S. Hassanpour, J. Sargent, C. M. Robinson, J. A. Doherty, and T. Onega, "Assessing data availability and quality within an electronic health record system through external validation against an external clinical data source," *BMC Med. Informat. Decis. Making*, vol. 19, no. 1, pp. 1–9, Dec. 2019.

[77] S. M. Meystre, F. J. Friedlin, B. R. South, S. Shen, and M. H. Samore, "Automatic de-identification of textual documents in the electronic health record: A review of recent research," *BMC Med. Res. Methodol.*, vol. 10, no. 1, pp. 1–16, Dec. 2010.
[78] M. Price, P. Bellwood, N. Kitson, I. Davies, J. Weber, and F. Lau, "Conditions potentially sensitive to a personal health record (PHR) intervention, a systematic review," *BMC Med. Informat. Decis. Making*, vol. 15, no. 1, pp. 1–12, Dec. 2015.
[79] M. Lluch, "Healthcare professionals' organisational barriers to health information technologies—A literature review," *Int. J. Med. Informat.*, vol. 80, no. 12, pp. 849–862, Dec. 2011.
[80] E. Deutsch, G. Duftschmid, and W. Dorda, "Critical areas of national electronic health record programs—Is our focus correct?" *Int. J. Med. Informat.*, vol. 79, no. 3, pp. 211–222, Mar. 2010.
[81] L. L. Fragidis and P. D. Chatzoglou, "Implementation of a nationwide electronic health record (EHR): The international experience in 13 countries," *Int. J. Health Care Qual. Assurance*, vol. 31, no. 2, pp. 116–130, Mar. 2018.
[82] P. Coorevits, M. Sundgren, G. O. Klein, A. Bahr, B. Claerhout, C. Daniel, M. Dugas, D. Dupont, A. Schmidt, P. Singleton, G. De Moor, and D. Kalra, "Electronic health records: New opportunities for clinical research," *J. Internal Med.*, vol. 274, no. 6, pp. 547–560, Dec. 2013.
[83] Z. Omary, D. Lupiana, F. Mtenzi, and B. Wu, "Challenges to e-healthcare adoption in developing countries: A case study of Tanzania," in *Proc. 1st Int. Conf. Netw. Digit. Technol.*, Jul. 2009, pp. 201–209.
[84] S. Kathryn, "Security and privacy implications of heathcare digitisation," Improving Future, Tech. Rep., 2011.
[85] D. M. Mugo and D. Nzuki, "Determinants of electronic health in developing countries," *Int. J. Arts Commerce*, 2014.
[86] H. M. Tun, "Analysis on conversion process from paper record ECG to computer based ECG," *MOJ Appl. Bionics Biomech.*, vol. 1, no. 2, pp. 1–11, Sep. 2017.
[87] A. M. Siika, J. K. Rotich, C. J. Simiyu, E. M. Kigotho, F. E. Smith, J. E. Sidle, K. Wools-Kaloustian, S. N. Kimaiyo, W. M. Nyandiko, T. J. Hannan, and W. M. Tierney, "An electronic medical record system for ambulatory care of HIV-infected patients in Kenya," *Int. J. Med. Informat.*, vol. 74, no. 5, pp. 345–355, Jun. 2005.
[88] H. Fraser, P. Biondich, D. Moodley, S. Choi, B. Mamlin, and P. Szolovits, "Implementing electronic medical record systems in developing countries," *J. Innov. Health Informat.*, vol. 13, no. 2, pp. 83–95, Jun. 2005.
[89] M. A. Alkureishi, W. W. Lee, M. Lyons, V. G. Press, S. Imam, A. Nkansah-Amankra, D. Werner, and V. M. Arora, "Impact of electronic medical record use on the patient–doctor relationship and communication: A systematic review," *J. Gen. Internal Med.*, vol. 31, pp. 548–560, May 2016.
[90] R. J. Chin, D. Sangmanee, and L. Piergallini, "PEPFAR funding and reduction in HIV infection rates in 12 focus sub-Saharan African countries: A quantitative analysis," *Int. J. MCH AIDS*, vol. 3, no. 2, p. 150, 2015.
[91] A. F. Klaib and M. S. Nuser, "Evaluating EHR and health care in Jordan according to the international health metrics network (HMN) framework and standards: A case study of Hakeem," *IEEE Access*, vol. 7, pp. 51457–51465, 2019.
[92] C. Schoen, R. Osborn, D. Squires, M. Doty, P. Rasmussen, R. Pierson, and S. Applebaum, "A survey of primary care doctors in ten countries shows progress in use of health information technology, less in other areas," *Health Affairs*, vol. 31, no. 12, pp. 2805–2816, Dec. 2012.
[93] G. De Moor, M. Sundgren, D. Kalra, A. Schmidt, M. Dugas, B. Claerhout, T. Karakoyun, C. Ohmann, P.-Y. Lastic, N. Ammour, R. Kush, D. Dupont, M. Cuggia, C. Daniel, G. Thienpont, and P. Coorevits, "Using electronic health records for clinical research: The case of the EHR4CR project," *J. Biomed. Informat.*, vol. 53, pp. 162–173, Feb. 2015.
[94] H. S. Fraser and J. Blaya, "Implementing medical information systems in developing countries, what works and what doesn't," in *Proc. AMIA Annu. Symp.* Bethesda, MD, USA: American Medical Informatics Association, 2010, p. 232.
[95] R. Ssembatya, A. Kayem, and G. Marsden, "On the challenge of adopting standard EHR systems in developing countries," in *Proc. 3rd ACM Symp. Comput. Develop.*, Jan. 2013, pp. 1–2.
[96] S. Ajami and R. Arab-Chadegani, "Barriers to implement electronic health records (EHRs)," *Materia Socio Medica*, vol. 25, no. 3, p. 213, 2013.
[97] J. Ross, F. Stevenson, R. Lau, and E. Murray, "Factors that influence the implementation of e-health: A systematic review of systematic reviews (an update)," *Implement. Sci.*, vol. 11, no. 1, pp. 1–12, Dec. 2016.
[98] F. Ahmad, P. L. Hudak, K. Bercovitz, E. Hollenberg, and W. Levinson, "Are physicians ready for patients with internet-based health information?" *J. Med. Internet Res.*, vol. 8, no. 3, p. e22, Sep. 2006.
[99] R. Ward, C. Stevens, P. Brentnall, and J. Briddon, "The attitudes of health care staff to information technology: A comprehensive review of the research literature," *Health Inf. Libraries J.*, vol. 25, no. 2, pp. 81–97, Jun. 2008.
[100] G. Fitzgerald, L. Piris, and A. Serrano, "Identification of benefits and barriers for the adoption of e-health information systems using a socio-technical approach," in *Proc. 30th Int. Conf. Inf. Technol. Interfaces (ITI)*, Jun. 2008, pp. 601–606.
[101] S. Z. Khan, Z. Shahid, K. Hedstrom, and A. Andersson, "Hopes and fears in implementation of electronic health records in Bangladesh," *Electron. J. Inf. Syst. Developing Countries*, vol. 54, no. 1, pp. 1–18, Oct. 2012.
[102] M. R. Hoque, A. Albar, and J. Alam, "Factors influencing physicians' acceptance of e-health in developing country: An empirical study," *Int. J. Healthcare Inf. Syst. Informat.*, vol. 11, no. 1, pp. 58–70, 2016.
[103] I. Ferraz and A. Guedes, "Protagonist-patient and servant-doctor: A medicine for the sick doctor-patient relationship," *Eur. Psychiatry*, vol. 41, no. S1, p. S683, 2017.
[104] S. Ebadollahi, A. R. Coden, M. A. Tanenblatt, S.-F. Chang, T. Syeda-Mahmood, and A. Amir, "Concept-based electronic health records: Opportunities and challenges," in *Proc. 14th ACM Int. Conf. Multimedia*, Oct. 2006, pp. 997–1006.
[105] K. Adams, J. Howe, A. Fong, J. Puthumana, K. Kellogg, M. Gaunt, and R. Ratwani, "An analysis of patient safety incident reports associated with electronic health record interoperability," *Appl. Clin. Informat.*, vol. 8, no. 2, pp. 593–602, Apr. 2017.
[106] L. Wong, K. W. Sexton, and J. A. Sanford, "The impact of an organization-wide electronic health record (EHR) system upgrade on Physicians' daily EHR activity time: An EHR log data study," *ACI Open*, vol. 6, no. 2, pp. e94–e97, Jul. 2022.
[107] T. D. Shanafelt, L. N. Dyrbye, C. Sinsky, O. Hasan, D. Satele, J. Sloan, and C. P. West, "Relationship between clerical burden and characteristics of the electronic environment with physician burnout and professional satisfaction," *Mayo Clinic Proc.*, vol. 91, no. 7, pp. 836–848, 2016.
[108] M. Tai-Seale, C. W. Olson, J. Li, A. S. Chan, C. Morikawa, M. Durbin, W. Wang, and H. S. Luft, "Electronic health record logs indicate that physicians split time evenly between seeing patients and desktop medicine," *Health Affairs*, vol. 36, no. 4, pp. 655–662, Apr. 2017.
[109] J. K. Wang, D. Ouyang, J. Hom, J. Chi, and J. H. Chen, "Characterizing electronic health record usage patterns of inpatient medicine residents using event log data," *PLoS ONE*, vol. 14, no. 2, Feb. 2019, Art. no. e0205379.
[110] R. Navigli, "Word sense disambiguation: A survey," *ACM Comput. Surv.*, vol. 41, no. 2, pp. 1–69, 2009.
[111] U. Hamiel, I. Hecht, A. Nemet, L. Pe'er, V. Man, A. Hilely, and A. Achiron, "Frequency, comprehension and attitudes of physicians towards abbreviations in the medical record," *Postgraduate Med. J.*, vol. 94, no. 1111, pp. 254–258, May 2018.
[112] V. K. Keloth, S. Zhou, A. J. Einstein, G. Elhanan, Y. Chen, J. Geller, and Y. Perl, "Generating training data for concept-mining for an 'interface terminology' annotating cardiology EHRs," in *Proc. IEEE Int. Conf. Bioinf. Biomed. (BIBM)*, Dec. 2020, pp. 1728–1735.
[113] M. Assale, L. G. Dui, A. Cina, A. Seveso, and F. Cabitza, "The revival of the notes field: Leveraging the unstructured content in electronic health records," *Frontiers Med.*, vol. 6, p. 66, Apr. 2019.
[114] M. Zhang, M. Luo, R. Nie, and Y. Zhang, "Technical attributes, health attribute, consumer attributes and their roles in adoption intention of healthcare wearable technology," *Int. J. Med. Informat.*, vol. 108, pp. 97–109, Dec. 2017.
[115] D. S. Carrell, R. E. Schoen, D. A. Leffler, M. Morris, S. Rose, A. Baer, S. D. Crockett, R. A. Gourevitch, K. M. Dean, and A. Mehrotra, "Challenges in adapting existing clinical natural language processing systems to multiple, diverse health care settings," *J. Amer. Med. Inform. Assoc.*, vol. 24, no. 5, pp. 986–991, Sep. 2017.

[116] H. Xu, P. D. Stetson, and C. Friedman, "A study of abbreviations in clinical notes," in *Proc. AMIA Annu. Symp.* Bethesda, MD, USA: American Medical Informatics Association, 2007, p. 821.

[117] V. Joopudi, B. Dandala, and M. Devarakonda, "A convolutional route to abbreviation disambiguation in clinical text," *J. Biomed. Informat.*, vol. 86, pp. 71–78, Oct. 2018.

[118] P. F. Brown, S. A. D. Pietra, V. J. D. Pietra, and R. L. Mercer, "Word-sense disambiguation using statistical methods," in *Proc. 29th Annu. Meeting Assoc. Comput. Linguistics*, 1991, pp. 264–270.

[119] A. Janz and M. Piasecki, "A weakly supervised word sense disambiguation for Polish using rich lexical resources," *Poznan Stud. Contemp. Linguistics*, vol. 55, no. 2, pp. 339–365, Jun. 2019.

[120] R. M. K. Sinha, "Learning disambiguation of Hindi morpheme 'vaalaa' with a sparse corpus," in *Proc. Int. Conf. Mach. Learn. Appl.*, Dec. 2009, pp. 653–657.

[121] D. Yarowsky, "Unsupervised word sense disambiguation rivaling supervised methods," in *Proc. 33rd Annu. Meeting Assoc. Comput. Linguistics*, 1995, pp. 189–196.

[122] R. Chasin, A. Rumshisky, O. Uzuner, and P. Szolovits, "Word sense disambiguation in the clinical domain: A comparison of knowledge-rich and knowledge-poor unsupervised methods," *J. Amer. Med. Inform. Assoc.*, vol. 21, no. 5, pp. 842–849, Sep. 2014.

[123] S. P. Ponzetto and R. Navigli, "Knowledge-rich word sense disambiguation rivaling supervised systems," in *Proc. 48th Annu. Meeting Assoc. Comput. linguistics*, 2010, pp. 1522–1531.

[124] S. Pakhomov, T. Pedersen, and C. G. Chute, "Abbreviation and acronym disambiguation in clinical discourse," in *Proc. AMIA Annu. Symp.* Bethesda, MD, USA: American Medical Informatics Association, 2005, p. 589.

[125] H. Xu, P. D. Stetson, and C. Friedman, "Combining corpus-derived sense profiles with estimated frequency information to disambiguate clinical abbreviations," in *Proc. AMIA Annu. Symp.* Bethesda, MD, USA: American Medical Informatics Association, 2012, p. 1004.

[126] S. Moon, S. Pakhomov, and G. B. Melton, "Automated disambiguation of acronyms and abbreviations in clinical texts: Window and training size considerations," in *Proc. AMIA Annu. Symp.* Bethesda, MD, USA: American Medical Informatics Association, 2012, p. 1310.

[127] G. P. Finley, S. V. Pakhomov, R. McEwan, and G. B. Melton, "Towards comprehensive clinical abbreviation disambiguation using machine-labeled training data," in *Proc. AMIA Annu. Symp.* Bethesda, MD, USA: American Medical Informatics Association, 2016, p. 560.

[128] A. Pesaranghader, S. Matwin, M. Sokolova, and A. Pesaranghader, "DeepBioWSD: Effective deep neural word sense disambiguation of biomedical text data," *J. Amer. Med. Inform. Assoc.*, vol. 26, no. 5, pp. 438–446, May 2019.

[129] Y. Wu, J. Xu, Y. Zhang, and H. Xu, "Clinical abbreviation disambiguation using neural word embeddings," in *Proc. BioNLP*, 2015, pp. 171–176.

[130] E. M. Polce and K. N. Kunze, "A guide for the application of statistics in biomedical studies concerning machine learning and artificial intelligence," *Arthroscopy, J. Arthroscopic Rel. Surg.*, vol. 39, no. 2, pp. 151–158, Feb. 2023.

[131] M. Skreta, A. Arbabi, J. Wang, E. Drysdale, J. Kelly, D. Singh, and M. Brudno, "Automatically disambiguating medical acronyms with ontology-aware deep learning," *Nature Commun.*, vol. 12, no. 1, p. 5319, Sep. 2021.

[132] G. K. Savova, J. J. Masanz, P. V. Ogren, J. Zheng, S. Sohn, K. C. Kipper-Schuler, and C. G. Chute, "Mayo clinical text analysis and knowledge extraction system (cTAKES): Architecture, component evaluation and applications," *J. Amer. Med. Inform. Assoc.*, vol. 17, no. 5, pp. 507–513, Sep. 2010.

[133] A. R. Aronson, "Effective mapping of biomedical text to the UMLS Metathesaurus: The MetaMap program," in *Proc. AMIA Symp.* Bethesda, MD, USA: American Medical Informatics Association, 2001, p. 17.

[134] A. R. Aronson and F.-M. Lang, "An overview of MetaMap: Historical perspective and recent advances," *J. Amer. Med. Inform. Assoc.*, vol. 17, no. 3, pp. 229–236, May 2010.

[135] K. Kirchhoff and A. M. Turner, "Unsupervised resolution of acronyms and abbreviations in nursing notes using document-level context models," in *Proc. 7th Int. Workshop Health Text Mining Inf. Anal.*, 2016, pp. 52–60.

[136] C. Li, L. Ji, and J. Yan, "Acronym disambiguation using word embedding," in *Proc. AAAI Conf. Artif. Intell.*, 2015, vol. 29, no. 1, pp. 1–2.

[137] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, "Distributed representations of words and phrases and their compositionality," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 26, 2013, pp. 1–9.

[138] J. Y. Nakayama, V. Hertzberg, and J. C. Ho, "Making sense of abbreviations in nursing notes: A case study on mortality prediction," in *Proc. AMIA Summits Transl. Sci.*, 2019, p. 275.

[139] A. Jaber and P. Martínez, "Disambiguating clinical abbreviations using pre-trained word embeddings," in *Proc. HEALTHINF*, 2021, pp. 501–508.

[140] V. Kumar, D. R. Recupero, D. Riboni, and R. Helaoui, "Ensembling classical machine learning and deep learning approaches for morbidity identification from clinical notes," *IEEE Access*, vol. 9, pp. 7107–7126, 2021.

[141] R. Socher, Y. Bengio, and C. D. Manning, "Deep learning for NLP (without magic)," in *Proc. Tutorial Abstr. ACL*, 2012, p. 5.

[142] S. Moon, S. Pakhomov, and G. Melton, "Clinical abbreviation sense inventory," Univ. Minnesota Digit. Conservancy, 2012. [Online]. Available: https://hdl.handle.net/11299/137703

[143] J. Kim, L. Gong, J. Khim, J. C. Weiss, and P. Ravikumar, "Improved clinical abbreviation expansion via non-sense-based approaches," in *Proc. Mach. Learn. Health*, 2020, pp. 161–178.

[144] J. Devlin, M.-W. Chang, K. Lee, and K. Toutanova, "BERT: Pre-training of deep bidirectional transformers for language understanding," 2018, *arXiv:1810.04805*.

[145] Z. Yang, Z. Dai, Y. Yang, J. Carbonell, R. R. Salakhutdinov, and Q. V. Le, "XLNet: Generalized autoregressive pretraining for language understanding," in *Proc. Adv. Neural Inf. Process. Syst.*, vol. 32, 2019, pp. 1–11.

[146] C.-X. Zhang, M.-L. Wang, and X.-Y. Gao, "Biomedical word sense disambiguation based on graph attention networks," *IEEE Access*, vol. 10, pp. 123328–123336, 2022.

[147] A. Jaber and P. Martínez, "Disambiguating clinical abbreviations using a one-fits-all classifier based on deep learning techniques," *Methods Inf. Med.*, vol. 61, no. S 01, pp. e28–e34, Jun. 2022.

[148] I. Li, M. Yasunaga, M. Y. Nuzumlalı, C. Caraballo, S. Mahajan, H. Krumholz, and D. Radev, "A neural topic-attention model for medical term abbreviation disambiguation," 2019, *arXiv:1910.14076*.

[149] Z. Wen, X. H. Lu, and S. Reddy, "MeDAL: Medical abbreviation disambiguation dataset for natural language understanding pretraining," 2020, *arXiv:2012.13978*.

[150] I. Li, J. Pan, J. Goldwasser, N. Verma, W. P. Wong, M. Y. Nuzumlalı, B. Rosand, Y. Li, M. Zhang, D. Chang, R. A. Taylor, H. M. Krumholz, and D. Radev, "Neural natural language processing for unstructured data in electronic health records: A review," *Comput. Sci. Rev.*, vol. 46, Nov. 2022, Art. no. 100511.

[151] C. A. Kushida, D. A. Nichols, R. Jadrnicek, R. Miller, J. K. Walsh, and K. Griffin, "Strategies for de-identification and anonymization of electronic health record data for use in multicenter research studies," *Med. Care*, vol. 50, pp. S82–S101, Jul. 2012.

[152] J. L. Fernández-Alemán, I. C. Señor, P. Á. O. Lozoya, and A. Toval, "Security and privacy in electronic health records: A systematic literature review," *J. Biomed. Informat.*, vol. 46, no. 3, pp. 541–562, Jun. 2013.

[153] Q.-S. Zhang and S.-C. Zhu, "Visual interpretability for deep learning: A survey," *Frontiers Inf. Technol. Electron. Eng.*, vol. 19, no. 1, pp. 27–39, Jan. 2018.

[154] A. Vellido, "The importance of interpretability and visualization in machine learning for applications in medicine and health care," *Neural Comput. Appl.*, vol. 32, no. 24, pp. 18069–18083, Dec. 2020.

[155] Z. Che, S. Purushotham, R. Khemani, and Y. Liu, "Distilling knowledge from deep networks with applications to healthcare domain," 2015, *arXiv:1512.03542*.

[156] C. Xiao, E. Choi, and J. Sun, "Opportunities and challenges in developing deep learning models using electronic health records data: A systematic review," *J. Amer. Med. Inform. Assoc.*, vol. 25, no. 10, pp. 1419–1428, Oct. 2018.

[157] A. Adadi and M. Berrada, "Peeking inside the black-box: A survey on explainable artificial intelligence (XAI)," *IEEE Access*, vol. 6, pp. 52138–52160, 2018.

[158] J. Mullenbach, S. Wiegreffe, J. Duke, J. Sun, and J. Eisenstein, "Explainable prediction of medical codes from clinical text," 2018, *arXiv:1802.05695*.

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