Inherent Bias in Electronic Health Records: A Scoping Review of Sources of Bias

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1 ABSTRACT

1.1 Objectives

Biases inherent in electronic health records (EHRs), which are often used as a data source to train medical AI models, may significantly exacerbate health inequities and challenge the adoption of ethical and responsible AI in healthcare. Biases arise from multiple sources, some of which are not as documented in the literature (e.g., bias in medical devices measurement). Biases are encoded in how the data has been collected and labeled, by implicit and unconscious biases of clinicians, or by the tools used for data processing. These biases and their encoding in healthcare records can potentially undermine the reliability of such data and bias clinical judgments and medical outcomes. Moreover, when healthcare records are used to build data-driven solutions, the biases can be further exacerbated, resulting in systems that can perpetuate biases and induce healthcare disparities. This literature scoping review aims to categorize the main sources of biases inherent in EHRs.

1.2 Methods

We queried PubMed and Web of Science on January 19th, 2023, for peer-reviewed sources in English, published between 2016 and 2023, using the PRISMA approach to stepwise scoping of the literature. To select the papers that empirically analyze bias in EHR, from the initial yield of 430 papers, 27 duplicates were removed, and 403 studies were screened for eligibility. 196 articles were removed after the title and abstract screening, and 96 articles were excluded after the full-text review resulting in a final selection of 116 articles.

1.3 Results

Existing studies often focus on individual biases in EHR data, but a comprehensive review categorizing these biases is largely absent. To address this gap, we propose a systematic taxonomy to classify and better understand the multiplicity of biases in EHR data. Our framework identifies six primary sources: a) bias from past *clinical trials*; b) *data-related biases*, such as missing

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or incomplete information; *human-related biases*, including c) implicit clinician bias, d) referral and admission bias, and e) diagnosis or risk disparities bias; and f) biases in devices and algorithms. This taxonomy, illustrated in Table 1, provides a valuable tool for systematically evaluating and addressing these issues.

1.4 Conclusions

Machine learning and data-driven solutions can potentially transform healthcare delivery, but not without limitations. The core inputs in the systems (data and human factors) currently contain several sources of bias that are poorly documented and analyzed for remedies. The current evidence heavily focuses on data-related biases, while other sources are less often analyzed or anecdotal. However, these different sources of bias can compound each other, leading to a cumulative effect. Therefore, to understand the issues holistically we need to explore these diverse sources of bias. While racial biases in EHR have been often documented, other sources of biases have been less frequently investigated and documented (e.g. gender-related biases, sexual orientation discrimination, socially induced biases, and implicit, often unconscious, human-related cognitive biases). Moreover, some existing studies lack concrete evidence of the effects of the bias, but rather illustrate the different prevalence of disease across groups, which does not *per se* prove the effect of the bias. Our review shows that data-, human- and machine biases are prevalent in healthcare and can significantly affect treatment decisions and outcomes and amplify healthcare disparities. Understanding how diverse biases affect AI systems and recommendations is critical. We recommend that researchers and medical personnel develop safeguards and adopt data-driven solutions with a "bias-in-mind" approach. More empirical evidence is needed to tease out the effects of different sources of bias on health outcomes.

CCS Concepts: • **Computing methodologies** → **Machine learning**; **Machine learning approaches**; • **Applied computing** → **Health care information systems**; **Health informatics**; • **Social and professional topics** → **Personal health records**; **Medical records**.

Additional Key Words and Phrases: Electronic Health Records (EHRs), AI Bias, Machine Learning (ML), Clinical Trial, Medical devices, Human Bias, Implicit bias

2 INTRODUCTION

In the United States, The Health Information Technology for Economic and Clinical Health Act [69], enacted in 2009, fueled innovation programs that promoted the use of EHRs in creating artificial intelligence (AI) solutions. Globally, similar programs have promoted the use of EHRs in algorithms and systems that aim to improve the operational and administrative efficiency of healthcare systems. In this review, we define Electronic Health Records (EHRs) as digital systems that capture, store, and manage comprehensive patient health information over time, including data from multiple clinical encounters, providers, and care settings. The exponential growth of patient data has opened up promising avenues for enhancing how physicians take care of their patients. In 2020 alone, around 2,314 exabytes of new data were generated in healthcare globally [127]. To improve efficiency in analyzing this vast amount of information and deriving actionable insights to enhance decision-making, AI is being increasingly used in healthcare. Many AI systems are trained on data collected in medical facilities, mainly EHRs which contain patients' medical history, while a portion of AI systems are trained on claims data. EHRs are typically maintained by a health provider over time and generally include the key administrative clinical data relevant to that person's care, including demographics, progress notes, problems, medications, vital signs, past medical history, immunizations, laboratory data, and radiology reports [72]. EHR data are known to carry a range of biases due to factors such as missingness, coding variability, and healthcare access disparities, all of which can impact downstream analyses and model development [4].

The training of AI models based on EHRs creates opportunities for improved efficiency in analyzing the vast amount of health data and for deriving actionable insights to enhance decision-making at a significantly lower cost. The benefits include early prediction of disease risks, forecasting prognosis and development of disease, identifying data patterns hidden to human eye, and providing personalized recommendations for optimizing the delivery of treatment to large amounts of patients (which would not be feasible otherwise due to the limited

availability of human resources). For example, AI can help screen significantly more accurately than human experts alone. Recent examples include the risk of dementia in the community [15]. It can also improve the prediction of long-term recurrence risks for patients with ischemic cerebrovascular events after discharge from the hospital [147]. Moreover, the adoption of AI-based solutions to classify skin lesions using images is superior to humans in the challenging task of diagnosing the fine-grained variability in the appearance of skin lesions [44]. AI-based solutions can also be used to diagnose diseases such as diabetic retinopathy in parts of the world where there are too few ophthalmologists to read the fundus photographs and to follow up with each diabetic patient [148].

However, while powerful, AI-based solutions are only as good at making judgments as the data they are based on and humans that interpret and oversee its results [123]. Consequently, models based on the evaluation of EHRs can be subject to different types of biases [18]. In this paper, we define the biases inherent in EHRs or medical AI as the presence of systematic errors, unintentional prejudices, and inaccuracies in medical data that can affect the quality and fairness of subsequent healthcare delivery and decision-making [57]. EHR may hold inherent biases that occur through how data is collected, analyzed, or used. These inherent biases may be hidden in the data as they have many different sources, which may be hard to identify or correct, but they are likely to exacerbate the biases that the users of such data make (AI, health systems, or health professionals). For example, EHRs can be subject to biases arising from (1) collecting, reporting, labeling, or designing EHRs [23], (2) biases arising from implicit, unconscious stereotypes that healthcare professionals or algorithm engineers have as humans [48] or (3) inherent biases in algorithms and machine learning (ML) models [138]. These diverse biases can produce systematic errors in the data used to train AI-based solutions, which in turn spread through the system and can exacerbate biased decision-making of healthcare professionals. As such, these biases can limit reliability, perpetuate disparities, and increase health inequities when developing data-driven solutions from biased EHRs to treat patients. Nevertheless, it remains to characterize the multiplicity of data sources from which biases can arise and to quantify how different sources biases affect healthcare outcomes. Finding potential remedies for the biases requires a deep understanding of its causes, which currently only surfaces in the literature [63].

The outcomes of biases are potentially grave. For example, disease misclassification occurs as a consequence of bias hindering machine learning models developed on EHRs [96]. A potential source of bias emerges from disparities in diagnosis and prognosis for patients with different demographic or societal/environmental attributes. In a study of all reported trials supporting FDA oncology drug approvals between 2008 and 2018, Black and Hispanic races are consistently underrepresented compared with their burden of cancer incidence [89]. Previous research has shown disparities in diagnosis between patients with different types of cancers [60] or differences in risk of HIV between Black and White men when accounting for confounding variables [60]. The use of EHR data to build models that predict health needs can introduce biases that reflect existing disparities in healthcare access rather than actual medical necessity. When proxy variables such as healthcare expenditures are used, they may misrepresent the needs of different populations, disproportionately favoring groups with greater access to care while disadvantaging others [108].

On top of more known sources of inherent bias in data, the literature also mentions less investigated sources such as the biases connected to the usage of medical devices/algorithms or implicit (and often unconscious) human biases when treating patients with different demographic characteristics [48]. These biases are sometimes perceived to originate from the measurement errors affecting medical devices, but at other times they are attributed rather to the differences in diagnoses or prognoses those devices create for patients with different demographic attributes. For example, significant variability was found in measurements of oxygen saturation levels for a given SpO2 level in Black patients relative to Hispanic, Asian, and White patients due to differences in how devices function on patients with different skin characteristics [144]. Although patients with or without hidden hypoxemia had similar clinical and demographic attributes, those with hidden hypoxemia had more comorbidities [71]. On the other hand, some studies showed that biased outcomes may also arise due to implicit, unconscious

human biases of healthcare professionals (due to stereotypes, prejudice, or other unconscious cognitive biases), which consequently negatively affect the quality of care [48]. Such biases may affect the referrals to treatment. For example, previous studies have shown a systematically lower percentage of preventive cervical cancer screening for lesbian/gay patients than for bisexual and heterosexual patients across five US federally qualified health centers [63].

From the current findings, it is unclear how sources of bias differ, what their idiosyncrasies are, and how to address these various biases. It remains unclear what exactly causes various biases and how they affect the decision-making of health professionals and AI systems. It does not help that the terminology related to biases is vast and varied such that different types of biases are confused in terminology, while biases coming from different sources are treated as synonyms, which further increases confusion. The identification of biases in the data used to train AI-based models is a key pillar for constructing fair and responsible AI to be used in decision-making. Therefore, identification of the sources of biases is an important step in developing solutions to address these biases. Indeed, in healthcare, growing attention is given to understanding responsible approaches to the development, implementation, management, and governance of AI [123].

This project aims to categorize the main sources of inherent biases in EHRs documented in the existing literature. In particular, the purpose of this scoping review is to answer the following questions:

(1) *What is the extent and nature of inherent bias in EHRs?*
(2) *What are the most prominent sources of these biases?*

A scoping review methodology was used [132] for a comprehensive overview of the existing literature on these topics. The authors of the manuscript bring a diverse range of perspectives and experience to this scoping review. The team includes a clinician and professor with extensive experience exploring bias in medicine, two researchers from business schools specializing in consumer technology interaction and bias, two information scientists with expertise in medical literature, and two computational informatics researchers. This combination of backgrounds supports a thoughtful and multidisciplinary approach to the review. To situate our new approach within a broader ethical context, we reference to the five-stage pipeline proposed by IY Chen et al. (2021), which highlights where bias can emerge—from problem selection to postdeployment. Our focus on biases inherent in EHRs aligns closely with the early stages of this pipeline, particularly data collection and outcome definition, where foundational decisions shape downstream fairness [29].

3 METHOD

This review was conducted and reported following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) [132], guided by the JBI Manual for Evidence Synthesis [6].

3.1 Protocol Registration

A protocol for this scoping review has been registered with OSF. The protocol is available at: https://osf.io/skdm7

3.2 Eligibility Criteria

The eligibility criteria for the selection of papers included in our systematic review of the literature were as follows: (1) articles must explore some type of bias that may affect EHRs, (2) be written in English, (3) published between 2016 and 2023 (since the major investigative work on AI biases started in 2016), (4) published in peer-reviewed journals, and (5) include empirical evidence of some form of bias. We included most study designs, from experimental and quasi-experimental study designs to randomized controlled trials, non-randomized controlled trials, before and after studies, interrupted time-series studies, analytical observational studies, and descriptive observational studies. We excluded opinion pieces, conceptual papers, and medical case studies as these can't

indicate a larger-scale phenomenon or statistically show the existence of bias. To narrow the search and identify the sources of bias in traditional clinical medicine, articles were also excluded if they focused on subjects outside the scope of this review, including psychiatry, psychology, dentistry, veterinary medicine, and medical education. The exclusion of psychiatry and psychology was based on their distinct methodologies, frameworks, and unique sources of bias, which differ significantly from those encountered in general clinical medicine.

3.3 Search Strategy

We applied the search strategy to two large databases, PubMed [24] and Web of Science, as their scope and coverage of the topics at hand are relevant and extensive, while PubMed indexes mostly medical papers, Web of Science would also include computer science papers, making these two sources complimentary in the context of this review topic. The initial query consisted of several key subject terms including and adjacent to: "Bias" in combination with terms such as "electronic health record," "EHR," "healthcare provider," "clinical dataset," "disparities," "racial," "ethnic," "implicit," "gender," "unconscious," "socioeconomic," "machine", "device", "measurement", etc. The queries aimed to cover diverse sources of bias that may be inherent in EHRs and the medical field. The final search strings used for each database are presented in Appendix A. These queries yielded roughly 8,000 search results. Hence, we iteratively added conjunctions and exclusions of topics out of scope for this review. After the first analysis of the title and abstract, articles discussing disparities in medical education, workplace or wage disparities of medical practitioners, and gender-related bias in surgical residency were excluded. We narrowed the search strategy to 2016-2023 to provide a time-relevant overview of the literature, as interest and resources invested in equitable care and fairness in machine learning has significantly increased in recent years [58]. In the next stages, while reviewing selected studies, we used the snowball sampling technique to identify relevant studies for our analysis that were referenced in included articles but which we missed in our initial search.

3.4 Study/Source of Evidence Selection

Based on the database query from the previous section, 410 articles were retrieved and uploaded to the "Covidence" systematic review management platform [35] for the review process. Key sources like seminal papers or papers which with high relevance to the topic were identified through discussion, from which minimal cross-referencing was conducted by the authors, resulting in 20 additional sources manually added to Covidence and thus a total of 430 studies. To provide unified criteria for the inclusion of sources, based on the readings and discussion among authors in our interdisciplinary team, we have defined broad categories of bias as those related to data, humans, and algorithms or devices. Of the 430 sources included for review, 27 duplicates were identified and removed, and 403 studies were screened for eligibility in two stages. First, titles and abstracts were screened for further analysis, with the main criteria being that the study analyzes some form of inherent bias (as identified earlier) in a medical context. This phase excluded 191 articles (Figure 1). Next, a full-text review was conducted on the remaining 212 articles. Sources were excluded based on the following criteria: 1. The study was not peer-reviewed; 2. Editorials, conceptual pieces without data, or a qualitative study design (n=21); 3. The topic was irrelevant to this study (n=6); 4. The study does not illustrate an inherent bias (n=24); and 5. The study shows prevalence or differences in groups of patients but it does not provide evidence of bias (n=45). All excluded papers were labeled by at least two reviewers, and any conflicts were discussed between any two reviewers and resolved by a third reviewer. Overall, this phase resulted in the exclusion of 96 articles. We note that the main reason why relatively many of the initial hits were excluded refers to the fact that articles did not test empirically for bias (n=69). This points out the deficit of empirical studies, despite the wide discussion of these issues. Eventually, 116 articles were included for the scoping review. The full inclusion process is displayed in Figure 1.

3.5 Data Extraction/Data Items

An analysis of the articles included, after applying the eligibility criteria and conducting a full-text review, revealed six categories of bias. These categories were identified through an iterative process, where initial themes were derived from the literature and refined as articles were mapped to them. Specific data items were extracted from each study, including: publication year, study design, research setting, type of bias investigated and source of bias.

The data items and coding structure were determined a priori in the protocol and refined during the review process. The categorization of bias sources into primary and secondary categories was conducted using inductive coding based on recurring themes and concepts across the literature. This thematic mapping was performed independently by two or more reviewers, with discrepancies discussed and resolved by consensus. The overall process followed the data charting guidance provided in the JBI Manual for Evidence Synthesis.

4 FINDINGS

4.1 Important terminology issues identified in the studies

The above analysis of studies offered important insights. We found that the terminology of the phenomena varies across disciplines, areas, and studies. While the term "inherent bias" is prominent in medicine, "machine bias" and its synonyms are used in engineering and computer science, and "systemic, algorithmic, or AI bias" are terms prominently used in social science. This variation indicates the need for a careful and broad selection of keywords and mechanisms when reviewing the phenomena.

4.2 Important methodological issues identified in the studies

The most prominent methodological issue we found across studies is that many using the term bias or claiming to study biases in healthcare often fail to employ suitable approaches for demonstrating the presence or impact of bias. One such method is instrumental variable analysis. As indicated above, most excluded studies (and related discussions among reviewers) concern studies showing the prevalence of a condition in different populations or other differences between groups. While biases certainly may arise from these differences, they do not unequivocally prove the bias itself or the cause of the bias. Merely showing differences in two populations (e.g., group A being more prone to an illness or less willing to receive treatment relative to group B) does not directly confirm inherent bias in EHRs or devices, as there is no link established between bias and subsequent health outcomes. We illustrate the issue with a well-known example from Obermeyer et al. (2019), which demonstrated how using overall (past) healthcare spending as a proxy for predicting (future) healthcare needs introduces bias. Because healthcare expenditures systematically differ across racial groups due to disparities in access to care, the algorithm disproportionately prioritized treatment for affluent White patients over Black patients with similar healthcare needs. This bias arose from a misrepresentation of healthcare need, as the proxy variable itself encoded existing disparities in the healthcare system [108]. Showing the resulting causal effect of using such a misrepresented proxy which would lead to a biased algorithm, that would in turn give biased predictions for some groups, is an example of proving inherent bias.

5 SOURCES OF BIAS IN EHRS

Through an in-depth analysis of the included 116 papers, co-authors of this study classified the papers into six main sources of bias: (a) clinical trial-induced biases, (b) missing, incomplete, or poor labeling biases; (c) implicit clinician biases, (d) referral and admission biases, (e) diagnosis, prognosis or risk disparities biases, and (f) medical devices (AI) biases. It is noteworthy to point out that diverse other names exist for these types of bias, which we reference in the text when discussing those biases. The prevalence of each type of bias among the selected 116 papers is presented in Table 1. We note that these different sources of bias are not mutually exclusive; they

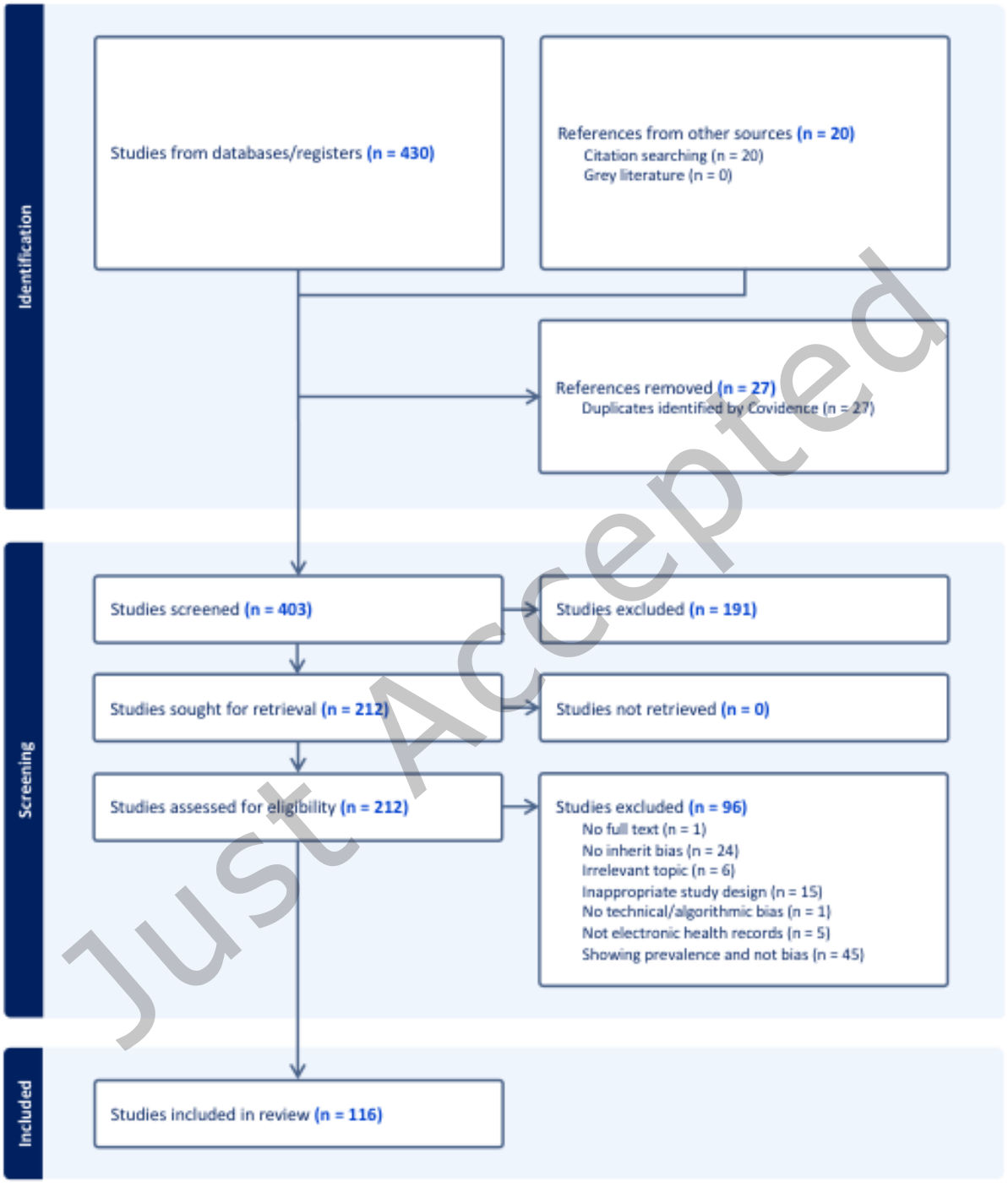

Fig. 1. PRiSMA exclusion flowchart: the flow chart describes the number of filtered articles and the reasons for exclusion

may overlap, lead to one another, or be otherwise interrelated. We have used these six categories holistically to show that biases differ in their sources, and these differences should be considered, both by researchers and practitioners.

Table 1. Types of bias and number of detected and screened publications.

Type	Form of Bias	n	Prevalence	References
Data-related Biases	Clinical Trial Induced Bias	5	4%	[14, 21, 43, 89, 112]
	Missing, Incomplete, Poor Logging of Information	14	12%	[3, 23, 33, 42, 57, 70, 75, 83, 86, 103, 106, 107, 111, 122, 129]
Human-induced Biases	Implicit Clinician Bias	19	16%	[9, 26, 31, 38, 39, 46, 48, 77, 78, 88, 113, 115, 125, 133, 134]
	Referral and Admission Bias	41	35%	[8, 12, 17, 20, 34, 36, 37, 40, 45, 46, 49, 50, 55, 62, 63, 67, 73, 74, 79–82, 84, 87, 91–95, 99, 101, 110, 116, 118, 121, 124, 126, 142, 143, 145, 146, 149]
	Diagnosis, Prognosis or Risk Disparities Bias	30	26%	[1, 10, 22, 25, 27, 32, 41, 52–54, 60, 64, 65, 68, 76, 85, 90, 97, 103, 120, 128, 135, 137, 139, 141]
Machine Bias	Medical devices Bias	9	8%	[5, 11, 13, 71, 109, 119, 130, 136]

5.1 Clinical trial-induced bias

Clinical trials stand as pivotal elements in medical research, crucial for the evaluation and validation of new therapeutic interventions, drugs, and standards of care. These studies systematically assess the impacts of specific interventions on human subjects by juxtaposing them with control groups, either untreated or given a placebo (i.e., a treatment without therapeutic effects investigated in the treatment, e.g. harmless pill) [117]. The ethical

and logistical challenges inherent in clinical trial recruitment necessitate not only enlisting a sufficient number of participants to ensure statistical power [61] but also striving for a sample that mirrors the diversity of the target population, who would ultimately benefit from the treatment under investigation [117]. This stage poses an ethical question to the study's conductor since the goal is to recruit an adequate number of participants to generate enough data to answer the research questions at hand, but it is usually impossible to choose a completely random sample group and at the same time representative of the general population or even the of the study's population [51]. This endeavor is crucial for minimizing *selection bias*, a form of bias that occurs when the trial population does not adequately represent the broader community, potentially skewing the trial's outcomes and applicability [66]. The concept of selection bias is closely related to those of *underrepresentation bias* or *informative presence bias*; sometimes, these concepts are even considered to be identical. The informative presence bias occurs in instances when those who have poorer health have more data recorded than healthier patients or in other similar instances when one patient group is represented more in the sample than other groups but this composition does not reflect the proportions in the general population of the studied disease[66]. As a result, employed AI-based solutions would prioritize patients in better-represented groups and make significant errors in the interpretation and prediction of the health needs of the underrepresented population, thereby further inducing healthcare disparities between these groups. In the identified literature, underrepresentation bias alone was shown to affect the decision thresholds, administration of care, or the medical procedure conducted in the study with no other plausible source of bias affecting the decision [14].

The under- and over-representation biases based on conclusions from previously conducted clinical trials come both from the self-selection in scientific publishing as well as the disparities in the socio-economic systems that define access to healthcare around the world. Publication bias, for instance, emerges from the tendency to publish studies with positive outcomes more frequently than those with negative or inconclusive results, leading to a skewed perception of an intervention's efficacy [98]. Another critical concern is the underrepresentation of certain demographic groups, either due to their scarcity in the general population or the presence of systemic barriers that deter participation and thereby create missing representation in the dataset. Such disparities can introduce "class imbalances," particularly detrimental in studies of rare diseases or for small communities with a certain sensitive feature on which AI bases prediction. This characteristic can significantly bias the development and evaluation of data-driven health solutions [131]. For example, AI models trained on datasets predominantly comprising data from one racial group are found not to perform accurately when applied to underrepresented groups [16]. The unrepresentativeness may occur due to the small samples (e.g. in minority populations), which may lead to underestimation or overestimation of risks in the subpopulation relative to the majority producing inaccurate or misleading recommendations. Deep learning algorithms used to predict acute kidney injury in adults significantly underperformed for female patients which represented just 6.4% of the data in the training dataset [129]. Similarly, the breast cancer survival rate algorithm underperformed for Black women which represented only 7.8% of the data [32]. Moreover, systematic reviews have highlighted significant gaps in the inclusion of racial and ethnic information in clinical research, underscoring the challenge of achieving representativeness [2]. Out of 38 studies that met the criteria of inclusion in the meta-analysis, 28 did include race/ethnicity information (73%), but only 17 studies (45%) included information on Hispanic participation while comprising a mere 11.6% of participants out of the general population tested [112]. A database study of all reported trials supporting FDA oncology drug approvals granted between July 2008 and June 2018 showed that only 63% of trials reported at least one race and 36.9% had no mention of race. In 7.8% of trials that reported results on four races (White, Asian, Black, or Hispanic), only White patients' representation matched their proportion based on cancer incidence and mortality in the United States, while Black and Hispanic populations were consistently underrepresented, and Asian overrepresented [89]. The disproportionality between clinical trial enrollment of certain ethnic minority groups and the prevalence of diseases among them is demonstrated empirically [14]. Less than 5% of African Americans participated in Diabetes mellitus clinical trials and only 32% took part in Antihypertensive and

Lipid-Lowering Treatment to Prevent Heart Attack Trial [14]. Participation in medication and therapy programs in the U.S. also indicated racial disparities, as patients with Alzheimer's disease and related dementias (ADRD) and diabetes were tested for their enrollment in the Medicare Medication Therapy Management (MTM) program. Significant disparities between White patients and Black patients were found within all study cohorts, as Black patients had significantly lower odds of enrolling in MTM programs compared to White patients [22]. Gender disparities are evident in the underrepresentation of women in cardiovascular trials. Only 33% to 38% of all clinical trials conducted between 2010-2020 consisted of women [14]. The lower participation rates of women in trials for hypertension, diabetes, hyperlipidemia, coronary artery disease, heart failure, and arrhythmia in recent years did not reflect the prevalence of these diseases in women.

This bias highlights the importance of systematically characterizing the composition of a trial or cohort and of comparing it to the state's or country's population. This step can help understand who is missing from the study and the analysis limitations. The repercussions of underrepresentation extend beyond the accuracy of clinical predictions to affect treatment paradigms and health outcomes across different population segments. Disparities in trial participation rates can lead to the development of treatment standards that do not adequately address the needs of all groups, particularly those historically marginalized or with limited access to healthcare resources [89]. Even more, the informative presence bias does not occur only between subjects, but also within-subject data when analyzing longitudinal patterns in the development of the disease. For example, longitudinal analyses of biomarkers are likely to show bias in hazard ratio estimates if biomarker values are analyzed predominantly based on informative visits (initiated by a patient), rather than noninformative visits (like routine check-ups). [59]. Even when both informative and noninformative visits are combined, the informative bias in biomarkers longitudinal analysis will form if the biomarkers are more volatile over time [66]. Addressing these challenges requires concerted efforts to enhance the inclusivity and equity of clinical research, ensuring that the benefits of medical advancements are accessible to all segments of society.

5.2 Missing and incomplete information

Missing or incomplete information and poor logging of information refer to bias arising from the quality of electronic health records used for research. EHRs are susceptible to biases stemming from missing, incomplete, or inaccurately logged information. These inaccuracies can arise from various factors such as medical staff oversight, technical issues in logging data, poor labeling, patient non-disclosure, or systemic constraints. This review identifies studies addressing the prevalence and implications of such data deficiencies.

Besides the fact that some of the subgroups in a population may intrinsically have smaller samples in the population, other important reasons for underrepresentation in databases may have intrinsically social causes which may lead to the lower representation of some groups in the databases due to the missing information. Examples include the underrepresentation of groups based on some structural barriers like the socioeconomic lack of access (for example, to medical care) or subpopulation's self-imposed exclusion due to the distrust in the system that may drive underrepresentation or other issues in self-reporting. Disparities in cancer diagnosis are found to be explainable by health insurance coverage, such that racial/ethnic minority children and adolescents are more likely to have an advanced cancer diagnosis compared with non-Hispanic White patients, which may relate to the lack of consistent healthcare access [140]. Neighborhood socioeconomic status (SES), rather than family SES, explained around 29% of racial disparities in the average rate of change in blood pressure trajectories for Black American versus non-Hispanic White preterm children [52]. Healthcare access due to social reasons, device allocation that differs between rural and urban areas or between hospitals, and measurement frequency which can be affected by the patient/doctor ratios or the location of the hospital, can all influence which patients will be included in the databases and with which likelihood [28].

In the realm of EHRs, a significant bias source is the inconsistent or erroneous recording of information, which can be seen as the labeling bias. For instance, discrepancies are found in the coding of Uveitis (an inflammation of the uvea, the middle layer of the eye) ICD10 across the two most prominent EHR systems (Epic and MDIntelleSys) yielding different codes in 13 out of 27 diseases [111]. Moreover, multiple codes were used to describe more than one specific disease. Therefore, combining data from different EHR systems can lead to fragmented and incomplete data and may affect downstream analysis and conclusion. Moreover, socioeconomic data is often unrecorded, and analyses based solely on complete cases introduce considerable selection bias [83]. This bias was evident in research on epithelial ovarian cancer, which indicated that missing data is not at random since the cases with missing data correlated with poorer survival outcomes [129]. Biases arising from missing or poor quality data are also likely to have led to disparities in healthcare services to LGBTQ patients [63]. Missingness and labeling biases can become amplified over time or in subsequent iterations of the data. Biases in EHR can skew large-scale studies, as illustrated by a study examining the time-varying biases in genome-wide association studies, which could lead to inaccurate gene-phenotype associations [122]. The secondary use of open databases is another concern, potentially generating biased machine learning models due to overlooked bias in data collection or processing, a phenomenon dubbed "data crime" [122]. Therefore, researchers who look to incorporate two or more datasets in model development to increase robustness and generalizability ultimately may introduce this form of bias into their model.

Data preparation adds another layer of complexity, introducing biases through labeling, coding, and the use of proxies for social categories. For example, differences in data labeling practices between Europe and the USA can significantly affect AI applications in pathology [105]. In the US, it is little known that some European staining solutions include saffron dye for improved fibrous tissue delineation, which may not even be indicated in the data description, since such information may be assumed as given [105]. Often different labeling terminology and standards are employed across countries, inducing variation and confusion in the use of terms and abbreviations. This issue extends to variations in clinical note-taking and terminology, which influence machine learning predictions in many hospital settings, including critical care mortality and psychiatric readmission [31]. Labeling biases and poor logging of information are likely to occur in numerous instances as medical professionals typically log information post-hoc and perceive these tasks as an administrative burden [102].

Even when data is labeled correctly, it is often not advisable to use some features or models that must use proxies of variables for the information that is missing. The use of proxies to circumvent the direct use of sensitive attributes like race, gender, and ethnicity in health predictions introduces measurement biases. A seminal study demonstrated that using healthcare costs as a proxy for healthcare needs led to a biased prioritization of White affluent patients over Black American patients with comparable disease burdens [108]. This example underscores the need for careful consideration in data handling and model development to prevent perpetuating existing health disparities.

5.3 Implicit Human Biases

Beyond the differential recording of clinical information across patient subgroups, healthcare practices also affect EHRs, influenced by the inherent, often unconscious biases of health professionals. These implicit biases entail the subconscious stereotypes healthcare providers hold, leading to skewed assessments of patient needs and medical conditions based on sensitive attributes such as race, gender, socioeconomic status, and medical history. These biases, which are typically involuntary and irrational, tend to be related to the implicit beliefs of healthcare professionals about the differences between genders, races, or ethnic minorities [48].

Healthcare professionals, like the general population, harbor implicit biases that reflect societal stereotypes about race, gender, and ethnicity. Such biases, inadvertently recorded in EHRs, contribute to perpetuating healthcare inequities. The training of medical students, which emphasizes pattern recognition and stereotypical

symptoms, may further embed these biases. Consequently, implicit bias adversely impacts diagnostic and treatment decisions, thereby exacerbating healthcare disparities. For instance, disparities in diagnosing malingering—where patients are unjustly accused of exaggerating medical issues—disproportionately affect men and Black patients [135]. Encoding such diagnosing in EHR has serious consequences on future medical care, the likelihood of admittance and receiving treatment.

Implicit biases have tangible consequences on medical care, particularly for marginalized groups such as ethnic minorities, immigrants, economically disadvantaged individuals, sexual minorities, and others, leading to systemic under-treatment and diagnostic inaccuracies. These biases manifest in various healthcare aspects, including initial disease diagnosis, and the timeliness and accuracy of diagnoses and treatments across several medical domains like neurodegenerative, pulmonary, cardiac diseases, and oncology [18, 86]. Implicit bias has been shown to lead to substantive physician errors in predicting heart attack such that physicians overtest predictably low-risk patients and under test predictably high-risk patients because they predominantly rely on simple heuristics like chest pain [104]. An AI model that learns from the resulting data will inevitably be biased in the same way.

Research also indicates that implicit biases contribute to significant physician errors, such as the misallocation of diagnostic resources based on simplistic heuristics rather than patient risk levels [125]. Patient reluctance to disclose information about prescribed medications to clinicians may signal mistrust stemming from previous experiences or the healthcare provider's perceived judgment about the patient's treatment adherence [31, 88].

5.4 Referral and admission bias (including access to care)

Biases related to clinician referrals and patient admissions significantly influence healthcare access and research participation. An admission bias arises when the selection criteria for research participation or medical care disproportionately exclude individuals based on discriminatory characteristics, leading to skewed study populations or unequal access to care [46]. Similarly, referral bias occurs due to systematic differences in who gets referred for further evaluation or treatment, often disadvantaging certain groups [36]. An example may be seen in studies that showed that minorities with worse objective dry eye parameters received fewer prescription treatments or procedures than White patients [36].

This review focused on identifying studies that highlighted disparities in access to care and referral patterns across different treatments, such as cancer prognosis, cardiovascular diseases, and appendicitis, based on sociodemographic factors rather than objective medical criteria. These barriers often stem from implicit biases and socioeconomic constraints, leading to delayed or foregone care [67, 127]. The impact of racial and socioeconomic status on access to care is well-documented, with minority groups and those from lower socioeconomic backgrounds facing significant barriers to receiving treatment and diagnoses at earlier, more treatable disease stages [16, 20]. Lower socioeconomic strata patients were diagnosed at a later stage of anal cancer disease, had worse survival than wealthier patients, and were less likely to receive radiation therapy [25].

Furthermore, studies have shown that disparities in care access and referral patterns manifest early in life, with children from African American backgrounds experiencing lower admission rates and follow-up care in intensive settings [62]. Gender disparities also contribute to these biases, affecting referral rates to specialists and hospital admissions [7]. For instance, young women are less likely to undergo certain procedures like percutaneous coronary intervention compared to their male counterparts, resulting in higher in-hospital adverse event rates [112].

Socioeconomic status further compounds these issues, with individuals from lower socioeconomic strata receiving suboptimal care for conditions such as blood pressure management [47]. These systematic biases not only impact patient outcomes but also influence the representation of diverse populations in clinical data, perpetuating biases in data-driven healthcare solutions.

In summary, implicit biases related to clinician referrals and patient admissions create significant barriers to equitable healthcare access and treatment. Addressing these biases requires concerted efforts to ensure that healthcare and research practices are inclusive and representative of the diverse populations they serve.

5.5 Diagnosis, prognosis, or risk disparities bias

In addition to the biases in admission and referral to further treatment, implicit biases also occur at the later stages of the patient's journey. Disparities in the diagnosis, prognosis, and risk assessment within medical datasets emerge as a critical form of inherent bias, significantly influenced by patient demographics such as gender, SES, and race. A notable body of research highlights these disparities, particularly in the context of cancer diagnosis and treatment initiation stages. For instance, disparities based on SES and racial groups are evident in the diagnosis and treatment of various cancers [25, 135, 140]. Specifically, racial and ethnic disparities have been documented in the delayed diagnosis of appendicitis among Black children, where delays were associated with prior emergency department visits and the absence of imaging during these visits [62].

Moreover, disparities in cancer diagnosis have been linked to differences in health insurance coverage, leading to advanced cancer diagnoses among racial/ethnic minority children and adolescents compared to their non-Hispanic White counterparts, attributed to inconsistent healthcare access [140]. Similarly, patients from lower socioeconomic backgrounds are diagnosed at later stages of diseases such as anal cancer, experiencing poorer outcomes and reduced access to treatments like radiation therapy [25]. The influence of neighborhood SES, as opposed to individual or family SES, accounts for a significant portion of the racial disparities observed in health outcomes, such as blood pressure trajectories among preterm children [52].

Access to healthcare and the allocation of medical devices, which varies between rural and urban locations or among different hospitals, along with disparities in the frequency of medical assessments, can dictate the inclusion of patients in medical databases, further perpetuating these biases [47].

Additionally, conditions such as insulin resistance have been shown to contribute to racial disparities in breast cancer prognosis, highlighting the complex interplay between medical conditions and demographic factors [53]. Heightened HIV risk is found among Black men compared to White men, underscoring the role of specific risk factors unique to different racial groups [60].

This review identified 30 studies (26%) showcasing this category of bias, marking it as the most prevalent type of bias encountered. Such findings underscore the urgent need for strategies to mitigate these disparities, ensuring equitable healthcare outcomes across all patient demographics.

5.6 Data bias in medical devices and algorithms

Medical devices bias stems from discrepancies in how algorithms are programmed and the calibration of devices, potentially leading to measurement inaccuracies for patients with diverse ethnic, physiological, and biological characteristics. This bias may arise from technical errors in medical equipment [109, 119, 130, 136] or from underlying differences in measurements due to factors not related to the patient's medical condition. Within medical facilities, patients undergo frequent automatic testing using equipment such as pulse oximeters, EKGs, ECGs, and thermometers, alongside semi-automatic tests involving healthcare professionals (e.g., hematology analyzers, biochemistry analyzers, scales, and blood glucose monitors). The outcomes of these assessments play a crucial role in patient evaluation and treatment planning.

We noted nine articles in this review highlighting this form of bias. Specifically, pulse oximeters exhibit reduced accuracy in patients with darker skin pigmentation, an issue attributed to device miscalibration and the lack of diversity in development phases [109, 119, 130, 136]. Similar disparities in device accuracy affecting measurements like oxygen saturation, body temperature, and blood pressure [47] have been documented, often resulting from insufficiently diverse calibration populations [28]. A systematic review of mechanical ventilation studies found

that AI applied to mechanical ventilation has limited external validation and model calibration, with a substantial risk of bias, significant gaps in reporting, and poor code and data availability [56]

Such discrepancies in device performance can introduce biases into clinical data, potentially influencing treatment decisions, such as the administration of supplemental oxygen or the preference for certain temperature measurement methods, thereby affecting diagnoses and treatments for specific racial subgroups. For example, studies have identified an increased risk of occult hypoxemia in Black patients compared to White patients with identical oxygen saturation measurements [119, 136].

Additionally, benign ethnic neutropenia (BEN), a condition where individuals (commonly of African, Middle Eastern, and West Indian descent) present with neutropenia (absolute neutrophil count < 1500/μL) without an increased infection risk, exemplifies bias stemming from physiological variances across different patient groups [5, 11]. The biased interpretation of such measurements or conditions may perpetuate sub-optimal care for specific patient demographics, further encoded into EHR systems, highlighting the critical need for regulatory agencies to address medical devices bias to ensure equitable healthcare delivery. In addition, substantial biases in AI algorithms arise due to implicit human biases of programmers who develop algorithms, similar to the implicit biases outlined for health professionals. It is well documented that experts in computer science and AI developers are a fairly homogeneous group with the mental mindset of a Western White male [19].

6 DISCUSSION

6.1 How diverse sources of biases can compound

In the preceding discussions, we have endeavored to delineate and exemplify various biases originating from distinct sources. Adopting a process-oriented perspective, we aim to elucidate how these diverse sources of biases can interact and can compound. Figure 2 conceptualizes a typical patient journey, highlighting how inherent biases might emerge at various junctures and proliferate over time within a technocratic framework that leverages data-driven AI systems in healthcare. This depiction underscores the cumulative nature of biases, illustrating their potential to compound and exacerbate disparities in patient care and outcomes within AI-enhanced healthcare environments.

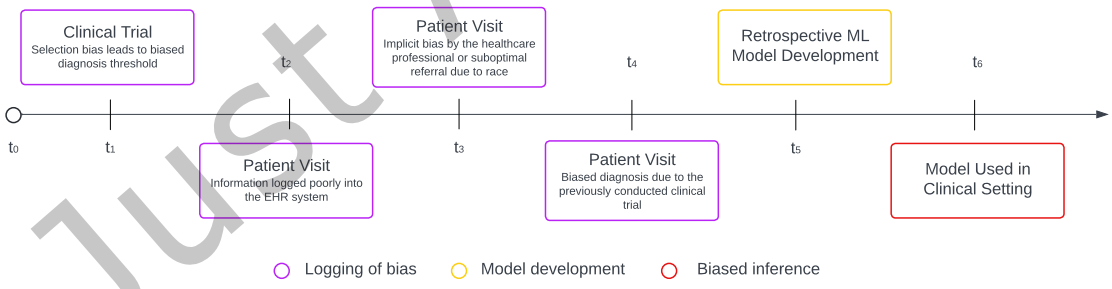

Fig. 2. Illustration of the source of bias on a timeline. A patient's timeline from inception. t_0 represents a clinical trial that results in a biased diagnosis threshold towards specific patient populations, and $t_1 - t_4$ represents the lifetime of a patient in the healthcare system until a particular time when the patient receives biased care due to implicit bias, or bias in medical devices. Incomplete information and biased clinical decisions are logged into the EHR system. At time t_5, a retrospective ML model is developed based on previously collected data. Which consequently results in biased inference, perpetuating the bias toward other patients

Consider a hypothetical patient, Annie, at the initial point in time, t_0, who begins experiencing symptoms necessitating a medical evaluation and possibly treatment. The primary step involves comparing their symptoms and medical history against existing knowledge and clinical trial data. Depending on Anne's ethnicity, gender, or socioeconomic status, she might find that the algorithms governing admission prioritize their case differently compared to other patients with similar symptoms. In the second stage, while waiting for admission, Anne might struggle with self-administered questionnaires, especially questions about their socioeconomic status and sexual orientation, due to their complexity or their reluctance to provide comprehensive responses. Objecting to these questions on moral grounds and privacy concerns, she decides to omit some answers and fabric some others. Subsequently, Anne meets with a healthcare professional who, despite their best intentions, appears significantly different from their in many respects, making it difficult for their to feel understood. This professional relies on an AI healthcare system that seems unable to fully "understand" them. The system, concurring with the doctor, diagnoses their in a manner that suggests she does not require hospital admission or further treatment. Left uncertain about their actual health risk despite their symptoms, Anne wonders if the system simply fails to recognize their unique needs. The patient is discharged, and the AI-based model, employing machine learning algorithms, records their case to refine future treatment predictions for similar cases. At the end of the shift, the doctor writes a very short note about Anne's case in the records. Despite Anne's experience, the hospital lauds the model for its operational efficiency.

6.2 Discussion of evidence

While this review aims to categorize and point out possible sources of hidden biases in EHRs, we emphasize this review serves only as a "call to action" and is far from covering the entire spectrum of biases currently residing in EHRs and medical data in general. This scoping review synthesizes the documented sources of bias in the current literature on EHRs, incorporating 116 articles that met the inclusion criteria. The review introduces inherent or hidden bias within EHR data, which poses significant challenges to developing machine learning models and the generalizability and precision of research findings. The inherent bias in EHRs can significantly affect retrospective studies and algorithmic model development. This review proposes a categorization of inherent bias into six distinct categories based on the source of bias: implicit clinician bias, bias in medical devices, disparities in diagnosis, prognosis or risk, referral and admission bias, biases resulting from clinical trials, and issues related to missing, incomplete, or poorly logged information. Increased discussion about potential sources of biases in healthcare has increased awareness, but diverse sources of bias identified in this review are still scarcely accounted for in research and development of AI-based solutions in healthcare.

The presence of these biases was consistent across various settings, populations, and EHR systems, indicating a broad applicability of this categorization framework. Notably, the review highlights the frequent misidentification or underreporting of bias types in the literature, where terms like disparities, equity, or differences in risk or prevalence in disease diagnosis often mask inherent bias.

The methodology of this review, grounded in clinical and human-machine interaction insights followed by a targeted literature search, has led to a focused and informative collection of articles. Referral and admission bias emerged as the most frequently documented category, suggesting that disparities in healthcare access—driven by factors like race, gender, and SES precede and influence the care process, thus introducing a selection bias in the development of machine learning models. The prominence of referral and admission bias reporting is understandable given that the objective data for analyzing this bias is more readily available. However, this finding also warns about the importance of providing empirical evidence on other sources of bias and the importance that transparency of databases and access to open sources have in the mitigation of AI biases.

The second most prevalent source of bias identified involves disparities in diagnosis, prognosis, or risk, highlighting how different risk factors and demographics can affect patient outcomes across various diseases, notably in oncology [25, 135]

Despite these challenges, advancements in artificial intelligence offer potential mitigations for human-induced biases. For instance, AI models have shown promise in addressing biases in radiographic measures and in recognizing the physical causes of pain across racial and socioeconomic groups, thereby accounting for a larger proportion of disparities in pain than traditional measures. For example, relative to standard measures of pain severity graded by radiologists, which accounted for only 9% of racial disparities in pain, AI predictions accounted for 43% of disparities, with similar results for lower-income and less-educated patients which stem from the racial and socioeconomic diversity of the training set [29].

This review underscores the critical need for awareness and corrective measures against inherent biases in EHR data to improve the fairness and effectiveness of machine learning applications in healthcare.

Addressing racial and other disparities due to data incompleteness is crucial for enhancing equity in health systems. Protocols and guidelines for routinely collecting and reporting disaggregated ethnicity data are recommended [18]. Initiatives like The HL7 Gravity project, which seeks to standardize social determinants of health measures for interoperable electronic health information exchange, are pivotal [100]. Synthetic data approaches in machine learning also play a vital role in compensating for the lack of diverse annotated medical data, ensuring analytical processes reflect the general population's diversity [30, 114].

Implicit clinician or healthcare provider bias represents a significant challenge, impacting ground truth (GT) for retrospective models and hindering the ability of models to eliminate existing biases. Addressing this requires educational interventions to increase awareness among medical students and practitioners [7]. Efforts to increase diversity within hospitals and medical schools may contribute to reducing such biases.

The literature indicates that machine or AI bias, resulting from historical biases in diagnoses, prognoses, and clinical decisions logged in EHRs, can be perpetuated by machine learning (ML) models. This underscores the necessity for critical evaluation of data and the acknowledgment of potential biases in medical devices, such as the differential risks indicated by pulse oximeters for patients of different races with identical readings [130], and varied infection risks for patients with BEN [11].

Furthermore, missing or poorly logged information in EHRs poses an additional source of inherent bias in EHR. This includes compatibility issues with ICD diagnosis codes across different EHR systems, which can introduce biases into ML models developed using data from multiple sources [111]. Researchers aiming to enhance model robustness and generalizability by integrating multiple datasets must navigate these challenges to avoid introducing biases.

6.3 Limitations

This scoping review is subject to several limitations that warrant careful consideration. Primarily, the inclusion of articles exclusively from PubMed and Web of Science introduces a potential database selection bias, potentially overlooking relevant research published in other languages or databases. Additionally, by focusing on peer-reviewed articles from 2016 to 2023, the review may omit earlier or more recent developments related to bias in electronic health records (EHRs). The exclusion of non-peer-reviewed literature could also contribute to publication bias, possibly exaggerating the prevalence of inherent bias, since the studies that show the bias may be more likely to get published than studies with inconclusive or nonsignificant results. Furthermore, the absence of a quality and rigor assessment for the included studies might impact the review's reliability. We also acknowledge our search did not include the term "Electronic Medical Record (EMR)," which may have excluded relevant studies using that terminology. Lastly, the generalizability of the findings is potentially limited, as the review may not encompass bias sources specific to certain demographics, healthcare environments, or

EHR systems. Future research should aim to mitigate these limitations and provide a more comprehensive understanding of bias in EHRs.

6.4 Conclusions

We approach these conclusions with epistemic humility, recognizing that the current evidence represents only an initial exploration of the challenges associated with EHRs. Due to the centralization of evidence in Western societies, a holistic understanding of global healthcare contexts, especially from underrepresented regions, remains elusive. This article aims to shed light on these inequities and encourage further research into the sources of bias embedded in global health records.

While data-driven tools offer opportunities to enhance efficiency and support clinical decision-making, their effectiveness depends heavily on the availability of accurate and representative data. Biases present in Electronic Health Records (EHRs) can inadvertently influence diagnostic accuracy and treatment outcomes.

Our review highlights six critical sources of "inherent biases" within EHRs that are often overlooked in the medical field: (a) implicit clinician bias, (b) bias in medical devices, (c) disparities in diagnosis or risk assessment, (d) referral and admission bias, (e) biases related to clinical trials, and (f) missing or incomplete information.

We suggest that clinicians and organizations implementing data-driven solutions carefully consider these biases and their potential impact on patient care. Addressing these challenges is essential for promoting equitable and reliable healthcare practices, fostering trust, and ensuring that technological advancements align with the diverse needs of global health systems.

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9 CONFLICTS OF INTEREST

The authors report no conflict of interest in this review

REFERENCES

[1] AA Adejare, Y Gautam, J Madzia, and TB Mersha. Unraveling racial disparities in asthma emergency department visits using electronic healthcare records and machine learning. *JOURNAL OF ASTHMA*, 59(1):79–93, 1 2022.

[2] Ritu Agarwal, Michelle Dugas, Jui Ramaprasad, Junjie Luo, Gujie Li, and Guodong Gao. Socioeconomic privilege and political ideology are associated with racial disparity in covid-19 vaccination. *Proceedings of the National Academy of Sciences*, 118(33):e2107873118, 2021.

[3] J Agor, OY Ozaltin, JS Ivy, M Capan, R Arnold, and S Romero. The value of missing information in severity of illness score development. *JOURNAL OF BIOMEDICAL INFORMATICS*, 97, 9 2019.

[4] Ban Al-Sahab, Alan Leviton, Tobias Loddenkemper, Nigel Paneth, and Bo Zhang. Biases in electronic health records data for generating real-world evidence: an overview. *Journal of Healthcare Informatics Research*, 8(1):121–139, 2024.

[5] Mohammed Shahriar Arefin, Alexander P Dumont, and Chetan A Patil. Monte carlo based simulations of racial bias in pulse oximetry. In *Design and Quality for Biomedical Technologies XV*, volume 11951, pages 8–12. SPIE, 2022.

[6] Edoardo Aromataris, Craig Lockwood, Kylie Porritt, Bianca Pilla, and Zoe Jordan, editors. *JBI Manual for Evidence Synthesis*. JBI, 2024.

[7] S Arya, C Franco-Mesa, and Y Erben. An analysis of gender disparities amongst united states medical students, general surgery residents, vascular surgery trainees, and the vascular surgery workforce. *JOURNAL OF VASCULAR SURGERY*, 75(1):5–9, 1 2022.

[8] Shipra Arya, Taylor A. Melanson, Elizabeth L. George, Kara A. Rothenberg, Manjula Kurella Tamura, Rachel E. Patzer, and Jason M. Hockenberry. Racial and sex disparities in catheter use and dialysis access in the united states medicare population. *Journal of the American Society of Nephrology : JASN*, 31(3):625–636, 3 2020. PMID: 31941721 PMCID: PMC7062210.

[9] Deborah Assayag, Julie Morisset, Kerri A. Johannson, Athol U. Wells, and Simon L. F. Walsh. Patient gender bias on the diagnosis of idiopathic pulmonary fibrosis. *Thorax*, 75(5):407–412, 5 2020. publisher-place: England PMID: 32054644.

[10] Suheil Albert Atallah-Yunes, Audrey Ready, and Peter E. Newburger. Benign ethnic neutropenia. *Blood Reviews*, 37:100586, 9 2019. PMID: 31255364 PMCID: PMC6702066.

[11] ZA Awan, SM Al Amoudi, M Saboor, and HY Alkhaldy. Isolated neutropenia/benign ethnic neutropenia: A common clinical and laboratory finding in southern and western saudi arabia. *INTERNATIONAL JOURNAL OF GENERAL MEDICINE*, 14:451–457, 2021.

[12] OA Babatunde, JM Eberth, TM Felder, R Moran, C Hughes-Halbert, S Truman, JR Hebert, S Heiney, and SA Adams. Racial disparities and diagnosis-to-treatment time among patients diagnosed with breast cancer in south carolina. *JOURNAL OF RACIAL AND ETHNIC HEALTH DISPARITIES*, 9(1):124–134, 2 2022.

[13] Jack Badawy, Oanh Kieu Nguyen, Christopher Clark, Ethan A. Halm, and Anil N. Makam. Is everyone really breathing 20 times a minute? assessing epidemiology and variation in recorded respiratory rate in hospitalised adults. *BMJ quality safety*, 26(10):832–836, 10 2017. PMID: 28652259 PMCID: PMC5812442.

[14] Sujana Balla, Sofia Elena Gomez, and Fatima Rodriguez. Disparities in cardiovascular care and outcomes for women from racial/ethnic minority backgrounds. *Current treatment options in cardiovascular medicine*, 22(12):75, 2020. PMID: 33223802 PMCID: PMC7669491.

[15] Nicasia Beebe-Wang, Alex Okeson, Tim Althoff, and Su-In Lee. Efficient and explainable risk assessments for imminent dementia in an aging cohort study. *IEEE Journal of Biomedical and Health Informatics*, 25(7):2409–2420, 2021.

[16] Nicasia Beebe-Wang, Alex Okeson, Tim Althoff, and Su-In Lee. Efficient and explainable risk assessments for imminent dementia in an aging cohort study. *IEEE Journal of Biomedical and Health Informatics*, 25(7):2409–2420, 7 2021. event-title: IEEE Journal of Biomedical and Health Informatics.

[17] A Blanken, CJ Gibson, YM Li, AJ Huang, AL Byers, S Maguen, S Inslicht, and K Seal. Racial/ethnic disparities in the diagnosis and management of menopause symptoms among midlife women veterans. *MENOPAUSE-THE JOURNAL OF THE NORTH AMERICAN MENOPAUSE SOCIETY*, 29(7):877–882, 7 2022.

[18] Andrew D. Boyd, Rosa Gonzalez-Guarda, Katharine Lawrence, Crystal L. Patil, Miriam O. Ezenwa, Emily C. O'Brien, Hyung Paek, Jordan M. Braciszewski, Oluwaseun Adeyemi, Allison M. Cuthel, Juanita E. Darby, Christina K. Zigler, P. Michael Ho, Keturah R. Faurot, Karen Staman, Jonathan W. Leigh, Dana L. Dailey, Andrea Cheville, Guilherme Del Fiol, Mitchell R. Knisely, Keith Marsolo, Rachel L. Richesson, and Judith M. Schlaeger. Equity and bias in electronic health records data. *Contemporary Clinical Trials*, 130:107238, 7 2023.

[19] Meredith Broussard. *More than a glitch: Confronting race, gender, and ability bias in tech.* MIT Press, 2023.

[20] Rachel-Maria Brown, Samia Tamazi, Catherine R. Weinberg, Aeshita Dwivedi, and Jennifer H. Mieres. Racial disparities in cardiovascular risk and cardiovascular care in women. *Current cardiology reports*, 24(9):1197–1208, 9 2022. publisher-place: United States PMID: 35802234.

[21] JA Browning, CCS Tsang, XB Dong, JY Wan, MA Chisholm-Burns, CK Finch, JW Tsao, CL Liu, and JL Wang. Effects of medicare comprehensive medication review on racial/ethnic disparities in nonadherence to statin medications among patients with alzheimer's disease: an observational analysis. *BMC HEALTH SERVICES RESEARCH*, 22(1), 2 2022.

[22] JA Browning, CCS Tsang, R Zeng, XB Dong, J Garuccio, JY Wan, MA Chisholm-Burns, CK Finch, JW Tsao, and JL Wang. Racial/ethnic disparities in the enrollment of medication therapy management programs among medicare beneficiaries with alzheimer's disease and related dementias. *CURRENT MEDICAL RESEARCH AND OPINION*, 38(10):1715–1725, 10 2022.

[23] Federico Cabitza, Davide Ciucci, and Raffaele Rasoini. A giant with feet of clay: On the validity of the data that feed machine learning in medicine. In *Organizing for the Digital World: IT for Individuals, Communities and Societies*, pages 121–136. Springer, 2019.

[24] Kathi Canese and Sarah Weis. Pubmed: the bibliographic database. *The NCBI handbook*, 2(1), 2013.

[25] KB Celie, C Jackson, S Agrawal, C Dodhia, C Guzman, T Kaufman, N Hellenthal, D Monie, J Monzon, and L Oceguera. Socioeconomic and gender disparities in anal cancer diagnosis and treatment. *SURGICAL ONCOLOGY-OXFORD*, 26(2):212–217, 6 2017.

[26] Damon Centola, Douglas Guilbeault, Urmimala Sarkar, Elaine Khoong, and Jingwen Zhang. The reduction of race and gender bias in clinical treatment recommendations using clinician peer networks in an experimental setting. *Nature communications*, 12(1):6585, 11 2021. PMID: 34782636 PMCID: PMC8593068.

[27] LC Chambers, CM Khosropour, DA Katz, JC Dombrowski, LE Manhart, and MR Golden. Racial/ethnic disparities in the lifetime risk of chlamydia trachomatis diagnosis and adverse reproductive health outcomes among women in king county, washington. *CLINICAL INFECTIOUS DISEASES*, 67(4):593–599, 8 2018.

[28] Marie-Laure Charpignon, Joseph Byers, Stephanie Cabral, Leo Anthony Celi, Chrystinne Fernandes, Jack Gallifant, Mary E. Lough, Donald Mlombwa, Lama Moukheiber, Bradley Ashley Ong, Anupol Panitchote, Wasswa William, An-Kwok Ian Wong, and Lama Nazer. Critical bias in critical care devices. *Critical Care Clinics*, 0(0), 3 2023. publisher: Elsevier.

[29] Irene Y Chen, Emma Pierson, Sherri Rose, Shalmali Joshi, Kadija Ferryman, and Marzyeh Ghassemi. Ethical machine learning in healthcare. *Annual review of biomedical data science*, 4(1):123–144, 2021.

[30] Richard J Chen, Ming Y Lu, Tiffany Y Chen, Drew FK Williamson, and Faisal Mahmood. Synthetic data in machine learning for medicine and healthcare. *Nature Biomedical Engineering*, 5(6):493–497, 2021.

[31] S Chung, QW Huang, J LaMori, D Doshi, and RJ Romanelli. Patient-reported experiences in discussing prescribed medications with a health care provider: Evidence for racial/ethnic disparities in a large health care delivery system. *POPULATION HEALTH MANAGEMENT*, 23(1):78–84, 2 2020.

[32] AE Connor, M Kaur, JY Sheng, and JH Hayes. Racial disparities in mortality outcomes among women diagnosed with breast cancer in maryland: Impact of cardiovascular disease and clinical characteristics. *CANCER*, 128(4):727–736, 2 2022.

[33] Lily A. Cook, Jonathan Sachs, and Nicole G. Weiskopf. The quality of social determinants data in the electronic health record: a systematic review. *Journal of the American Medical Informatics Association : JAMIA*, 29(1):187–196, 12 2021. PMID: 34664641 PMCID: PMC8714289.

[34] RB Correia, LPD Kohler, MM Mattos, and LM Rocha. City-wide electronic health records reveal gender and age biases in administration of known drug-drug interactions. *NPJ DIGITAL MEDICINE*, 2, 7 2019.

[35] Covidence. Covidence - better systematic review management. https://www.covidence.org, 2025. Accessed: 2025-01-11.

[36] David Cui, Priya M Mathews, Gavin Li, Lee Guo, Shanna VanCourt, Ian J Saldanha, and Esen Karamursel Akpek. Racial and ethnic disparities in dry eye diagnosis and care. *Ophthalmic Epidemiology*, 30(5):484–491, 2023.

[37] M Daher, M Al Rifai, RY Kherallah, F Rodriguez, D Mahtta, ED Michos, SU Khan, LA Petersen, and SS Virani. Gender disparities in difficulty accessing healthcare and cost-related medication non-adherence: The cdc behavioral risk factor surveillance system (brfss) survey. *PREVENTIVE MEDICINE*, 153, 12 2021.

[38] Rachel A Dahl, J Priyanka Vakkalanka, Karisa K Harland, and Joshua Radke. Investigating healthcare provider bias toward patients who use drugs using a survey-based implicit association test: Pilot study. *Journal of addiction medicine*, 16(5):557–562, 2022.

[39] Stacie L. Daugherty, Irene V. Blair, Edward P. Havranek, Anna Furniss, L. Miriam Dickinson, Elhum Karimkhani, Deborah S. Main, and Frederick A. Masoudi. Implicit gender bias and the use of cardiovascular tests among cardiologists. *Journal of the American Heart Association*, 6(12), 11 2017. PMID: 29187391 PMCID: PMC5779009.

[40] MM Donneyong, MA Fischer, MA Langston, JJ Joseph, PD Juarez, P Zhang, and DM Kline. Examining the drivers of racial/ethnic disparities in non-adherence to antihypertensive medications and mortality due to heart disease and stroke: A county-level analysis. *INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH AND PUBLIC HEALTH*, 18(23), 12 2021.

[41] Xianglin Du. Racial disparities in health insurance, triple-negative breast cancer diagnosis, tumor stage, treatment and survival in a large nationwide seer cohort in the united states. *Molecular and clinical oncology*, 16(4):1–12, 2022.

[42] HR Duenas, C Seah, JS Johnson, and LM Huckins. Implicit bias of encoded variables: frameworks for addressing structured bias in ehr-gwas data. *HUMAN MOLECULAR GENETICS*, 29(R1):R33–R42, 9 2020.

[43] J. H. Ellenberg. Selection bias in observational and experimental studies. *Statistics in Medicine*, 13(5-7):557–567, 4 1994. PMID: 8023035.

[44] Andre Esteva, Brett Kuprel, Roberto A Novoa, Justin Ko, Susan M Swetter, Helen M Blau, and Sebastian Thrun. Dermatologist-level classification of skin cancer with deep neural networks. *nature*, 542(7639):115–118, 2017.

[45] Albert J Farias, Gabriela Toledo, Carol Y Ochoa, and Ann S Hamilton. Racial/ethnic disparities in patient experiences with health care in association with earlier stage at colorectal cancer diagnosis: findings from the seer-cahps data. *Medical Care*, 59(4):295–303, 2021.

[46] A Farrukh and J Mayberry. Apparent disparities in hospital admission and biologic use in the management of inflammatory bowel disease between 2014-2018 in some black and ethnic minority (bem) populations in england (vol 2, pg 144, 2020). *GASTROINTESTINAL DISORDERS*, 3(3):127–128, 9 2021.

[47] Aaron Findley. Low health literacy and older adults: meanings, problems, and recommendations for social work. *Social work in health care*, 54(1):65–81, 2015. publisher-place: United States PMID: 25588097.

[48] Chloë FitzGerald and Samia Hurst. Implicit bias in healthcare professionals: a systematic review. *BMC Medical Ethics*, 18(1):19, 12 2017.

[49] V Fontil, L Pacca, BK Bellows, E Khoong, CE McCulloch, M Pletcher, and K Bibbins-Domingo. Association of differences in treatment intensification, missed visits, and scheduled follow-up interval with racial or ethnic disparities in blood pressure control. *JAMA CARDIOLOGY*, 7(2):204–212, 2 2022.

[50] Peter Franks and Kevin Fiscella. Effect of patient socioeconomic status on physician profiles for prevention, disease management, and diagnostic testing costs. *Medical Care*, 40(8):717–724, 8 2002. PMID: 12187185.

[51] Lawrence M. Friedman, Curt D. Furberg, David L. DeMets, David M. Reboussin, and Christopher B. Granger. *Fundamentals of Clinical Trials*. Springer International Publishing, Cham, 2015. DOI: 10.1007/978-3-319-18539-2.

[52] TE Fuller-Rowell, DS Curtis, PK Klebanov, J Brooks-Gunn, and GW Evans. Racial disparities in blood pressure trajectories of preterm children: The role of family and neighborhood socioeconomic status. *AMERICAN JOURNAL OF EPIDEMIOLOGY*, 185(10):888–897, 5 2017.

[53] Emily J. Gallagher, Kezhen Fei, Sheldon M. Feldman, Elisa Port, Neil B. Friedman, Susan K. Boolbol, Brigid Killelea, Melissa Pilewskie, Lydia Choi, Tari King, Anupma Nayak, Rebeca Franco, Daliz Cruz, Irini M. Antoniou, Derek LeRoith, and Nina A. Bickell. Insulin resistance contributes to racial disparities in breast cancer prognosis in us women. *Breast cancer research : BCR*, 22(1):40, 5 2020. PMID: 32393319 PMCID: PMC7216707.

[54] Emily J Gallagher, Giampaolo Greco, Sylvia Lin, Radhi Yagnik, Sheldon M Feldman, Elisa Port, Neil B Friedman, Susan K Boolbol, Brigid Killelea, Melissa Pilewskie, et al. Insulin resistance and racial disparities in breast cancer prognosis: a multi-center cohort study.

Endocrine-related cancer, 29(12):693–701, 2022.

[55] A Gallegos, R Dudovitz, C Biely, PJ Chung, TR Coker, E Barnert, AD Guerrero, PG Szilagyi, and BB Nelson. Racial disparities in developmental delay diagnosis and services received in early childhood. *ACADEMIC PEDIATRICS*, 21(7):1230–1238, 9 2021.

[56] Jack Gallifant, Joe Zhang, Maria del Pilar Arias Lopez, Tingting Zhu, Luigi Camporota, Leo A Celi, and Federico Formenti. Artificial intelligence for mechanical ventilation: systematic review of design, reporting standards, and bias. *British Journal of Anaesthesia*, 128(2):343–351, 2022.

[57] Milena A. Gianfrancesco, Suzanne Tamang, Jinoos Yazdany, and Gabriela Schmajuk. Potential biases in machine learning algorithms using electronic health record data. *JAMA internal medicine*, 178(11):1544–1547, 11 2018. PMID: 30128552 PMCID: PMC6347576.

[58] Judy Wawira Gichoya, Liam G McCoy, Leo Anthony Celi, and Marzyeh Ghassemi. Equity in essence: a call for operationalising fairness in machine learning for healthcare. *BMJ health & care informatics*, 28(1), 2021.

[59] Benjamin A Goldstein, Matthew Phelan, Neha J Pagidipati, and Sarah B Peskoe. How and when informative visit processes can bias inference when using electronic health records data for clinical research. *Journal of the American Medical Informatics Association*, 26(12):1609–1617, 2019.

[60] ND Goldstein, I Burstyn, and SL Welles. Bayesian approaches to racial disparities in hiv risk estimation among men who have sex with men. *EPIDEMIOLOGY*, 28(2):215–220, 3 2017.

[61] Rebecca F Gottesman and Roy Hamilton. Recruiting diverse populations in clinical trials: how do we overcome selection bias?, 2021.

[62] Monika K. Goyal, James M. Chamberlain, Michael Webb, Robert W. Grundmeier, Tiffani J. Johnson, Scott A. Lorch, Joseph J. Zorc, Evaline Alessandrini, Lalit Bajaj, Lawrence Cook, and Elizabeth R. Alpern. Racial and ethnic disparities in the delayed diagnosis of appendicitis among children. *Academic emergency medicine : official journal of the Society for Academic Emergency Medicine*, 28(9):949–956, 9 2021. publisher-place: United States PMID: 32991770.

[63] C Grasso, H Goldhammer, RJ Brown, and BW Furness. Using sexual orientation and gender identity data in electronic health records to assess for disparities in preventive health screening services. *INTERNATIONAL JOURNAL OF MEDICAL INFORMATICS*, 142, 10 2020.

[64] V Gupta, I Haque, J Chakraborty, S Graff, S Banerjee, and SK Banerjee. Racial disparity in breast cancer: can it be mattered for prognosis and therapy. *JOURNAL OF CELL COMMUNICATION AND SIGNALING*, 12(1):119–132, 3 2018.

[65] D Hardy and DIY Du. Socioeconomic and racial disparities in cancer stage at diagnosis, tumor size, and clinical outcomes in a large cohort of women with breast cancer, 2007-2016. *JOURNAL OF RACIAL AND ETHNIC HEALTH DISPARITIES*, 8(4):990–1001, 8 2021.

[66] Joanna Harton, Nandita Mitra, and Rebecca A Hubbard. Informative presence bias in analyses of electronic health records-derived data: a cautionary note. *Journal of the American Medical Informatics Association*, 29(7):1191–1199, 7 2022.

[67] Shaakir Hasan, Stanislav Lazarev, Madhur Garg, Keyur Mehta, Robert H Press, Arpit Chhabra, J Isabelle Choi, Charles B Simone, and Daniel Gorovets. Racial inequity and other social disparities in the diagnosis and management of bladder cancer. *Cancer Medicine*, 12(1):640–650, 2023.

[68] Y Hashimoto, M Shiina, P Dasgupta, P Kulkarni, T Kato, RK Wong, Y Tanaka, V Shahryari, S Yamamura, S Saini, GR Deng, ZL Tabatabai, S Majid, and R Dahiya. Upregulation of mir-130b contributes to risk of poor prognosis and racial disparity in african-american prostate cancer. *CANCER PREVENTION RESEARCH*, 12(9):585–598, 9 2019.

[69] "HealthIT.gov". Laws, regulation, and policy | healthit.gov. [Online; accessed 2023-12-17].

[70] Samuel Henly, Gaurav Tuli, Sheryl A. Kluberg, Jared B. Hawkins, Quynh C. Nguyen, Aranka Anema, Adyasha Maharana, John S. Brownstein, and Elaine O. Nsoesie. Disparities in digital reporting of illness: A demographic and socioeconomic assessment. *Preventive medicine*, 101:18–22, 8 2017. PMID: 28528170 PMCID: PMC5553633.

[71] NR Henry, AC Hanson, PJ Schulte, NS Warner, MN Manento, TJ Weister, and MA Warner. Disparities in hypoxemia detection by pulse oximetry across self-identified racial groups and associations with clinical outcomes*. *CRITICAL CARE MEDICINE*, 50(2):204–211, 2 2022.

[72] Alexander Hoerbst and Elske Ammenwerth. Electronic health records. *Methods of information in medicine*, 49(04):320–336, 2010.

[73] JA Holmes and RC Chen. Racial disparities in time from diagnosis to treatment for stage i non-small cell lung cancer. *JNCI CANCER SPECTRUM*, 2(1), 1 2018.

[74] D Islek, MK Ali, A Manatunga, A Alonso, and V Vaccarino. Racial disparities in hospitalization among patients who receive a diagnosis of acute coronary syndrome in the emergency department. *JOURNAL OF THE AMERICAN HEART ASSOCIATION*, 11(19), 10 2022.

[75] YZ Jin, S Schneeweiss, D Merola, and KJ Lin. Impact of longitudinal data-completeness of electronic health record data on risk score misclassification. *JOURNAL OF THE AMERICAN MEDICAL INFORMATICS ASSOCIATION*, 29(7):1225–1232, 6 2022.

[76] M. M. Joffe. Confounding by indication: the case of calcium channel blockers. *Pharmacoepidemiology and Drug Safety*, 9(1):37–41, 1 2000. PMID: 19025800.

[77] Tiffani J. Johnson, Daniel G. Winger, Robert W. Hickey, Galen E. Switzer, Elizabeth Miller, Margaret B. Nguyen, Richard A. Saladino, and Leslie R. M. Hausmann. Comparison of physician implicit racial bias toward adults versus children. *Academic pediatrics*, 17(2):120–126, 3 2017. PMID: 27620844 PMCID: PMC5337439.

[78] DD Jones. Examining the unconscious racial biases and attitudes of physicians, nurses, and the public: Implications for future health care education and practice. *HEALTH EQUITY*, 6(1):375–381, 5 2022.

[79] YJ Juhn, E Ryu, CI Wi, KS King, M Malik, S Romero-Brufau, CH Weng, S Sohn, RR Sharp, and JD Halamka. Assessing socioeconomic bias in machine learning algorithms in health care: a case study of the houses index. *JOURNAL OF THE AMERICAN MEDICAL INFORMATICS ASSOCIATION*, 29(7):1142–1151, 6 2022.

[80] EJ Kim, T Kim, J Conigliaro, JM Liebschutz, MK Paasche-Orlow, and AD Hanchate. Racial and ethnic disparities in diagnosis of chronic medical conditions in the usa. *JOURNAL OF GENERAL INTERNAL MEDICINE*, 33(7):1116–1123, 7 2018.

[81] BL Kinlock, RJ Thorpe, DL Howard, JV Bowie, LE Ross, DO Fakunle, and TA LaVeist. Racial disparity in time between first diagnosis and initial treatment of prostate cancer. *CANCER CONTROL*, 23(1):47–51, 1 2016.

[82] N Lamba, E Mehanna, RB Kearney, PJ Catalano, DA Haas-Kogan, BM Alexander, DN Cagney, KA Lee, and AA Aizer. Racial disparities in supportive medication use among older patients with brain metastases: a population-based analysis. *NEURO-ONCOLOGY*, 22(9):1339–1347, 9 2020.

[83] S Lamy, F Molinie, L Daubisse-Marliac, A Cowppli-Bony, S Ayrault-Piault, E Fournier, AS Woronoff, C Delpierre, and P Grosclaude. Using ecological socioeconomic position (sep) measures to deal with sample bias introduced by incomplete individual-level measures: inequalities in breast cancer stage at diagnosis as an example. *BMC PUBLIC HEALTH*, 19, 7 2019.

[84] Bruce E. Landon, Jukka-Pekka Onnela, Laurie Meneades, A. James O'Malley, and Nancy L. Keating. Assessment of racial disparities in primary care physician specialty referrals. *JAMA network open*, 4(1):e2029238, 1 2021. PMID: 33492373 PMCID: PMC7835717.

[85] D. R. Lannin, H. F. Mathews, J. Mitchell, M. S. Swanson, F. H. Swanson, and M. S. Edwards. Influence of socioeconomic and cultural factors on racial differences in late-stage presentation of breast cancer. *JAMA*, 279(22):1801–1807, 6 1998. PMID: 9628711.

[86] AJ Larrazabal, N Nieto, V Peterson, DH Milone, and E Ferrante. Gender imbalance in medical imaging datasets produces biased classifiers for computer-aided diagnosis. *PROCEEDINGS OF THE NATIONAL ACADEMY OF SCIENCES OF THE UNITED STATES OF AMERICA*, 117(23):12592–12594, 6 2020.

[87] O Lediju, J Ikuemonisan, SS Salami, and O Adejoro. Racial disparities in the presentation, early definitive surgical treatment, and mortality among men diagnosed with poorly differentiated/undifferentiated non-metastatic prostate cancer in the usa. *JOURNAL OF RACIAL AND ETHNIC HEALTH DISPARITIES*, 6(2):401–408, 4 2019.

[88] Ian Litchfield, Naiem Moiemen, and Sheila Greenfield. Barriers to evidence-based treatment of serious burns: The impact of implicit bias on clinician perceptions of patient adherence. *Journal of burn care research : official publication of the American Burn Association*, 41(6):1297–1300, 11 2020. publisher-place: England PMID: 32645716.

[89] Jonathan M. Loree, Seerat Anand, Arvind Dasari, Joseph M. Unger, Anirudh Gothwal, Lee M. Ellis, Gauri Varadhachary, Scott Kopetz, Michael J. Overman, and Kanwal Raghav. Disparity of race reporting and representation in clinical trials leading to cancer drug approvals from 2008 to 2018. *JAMA Oncology*, 5(10):e191870, 10 2019.

[90] Z Kevin Lu, Xiaomo Xiong, Xinyuan Wang, and Jun Wu. Gender disparities in anti-dementia medication use among older adults: Health equity considerations and management of alzheimer's disease and related dementias. *Frontiers in Pharmacology*, 12:706762, 2021.

[91] Y Luo, H Carretta, I Lee, G LeBlanc, D Sinha, and G Rust. Naive bayesian network-based contribution analysis of tumor biology and healthcare factors to racial disparity in breast cancer stage-at-diagnosis. *HEALTH INFORMATION SCIENCE AND SYSTEMS*, 9(1), 9 2021.

[92] J Lv, L Ni, KX Liu, XJ Gao, JG Yang, X Zhang, YQ Ye, QT Dong, R Fu, H Sun, XX Yan, YY Zhao, Y Wang, YJ Yang, and HY Xu. Clinical characteristics, prognosis, and gender disparities in young patients with acute myocardial infarction. *FRONTIERS IN CARDIOVASCULAR MEDICINE*, 8, 8 2021.

[93] R Mallick, RB Xie, JK Kirklin, H Chen, and CJ Balentine. Race and gender disparities in access to parathyroidectomy: A need to change processes for diagnosis and referral to surgeons. *ANNALS OF SURGICAL ONCOLOGY*, 28(1):476–483, 1 2021.

[94] K. McCaffery, J. Wardle, M. Nadel, and W. Atkin. Socioeconomic variation in participation in colorectal cancer screening. *Journal of Medical Screening*, 9(3):104–108, 2002. PMID: 12370320.

[95] UC Megwalu and YF Ma. Racial disparities in oropharyngeal cancer stage at diagnosis. *ANTICANCER RESEARCH*, 37(2):835–839, 2 2017.

[96] UC Megwalu and YF Ma. Racial/ethnic disparities in use of high-quality hospitals among thyroid cancer patients. *CANCER INVESTIGATION*, 39(6-7):482–488, 8 2021.

[97] Rajendra H. Mehta, David M. Shahian, Shubin Sheng, Sean M. O'Brien, Fred H. Edwards, Jeffery P. Jacobs, and Eric D. Peterson. Association of hospital and physician characteristics and care processes with racial disparities in procedural outcomes among contemporary patients undergoing coronary artery bypass grafting surgery. *Circulation*, 133(2):124–130, 1 2016. publisher-place: United States PMID: 26603032.

[98] Chloe Mirzayi, Audrey Renson, Genomic Standards Consortium, Massive Analysis, Quality Control Society Furlanello Cesare 31 Sansone Susanna-Assunta 84, Fatima Zohra, Shaimaa Elsafoury, Ludwig Geistlinger, Lora J Kasselman, Kelly Eckenrode, Janneke van de Wijgert, et al. Reporting guidelines for human microbiome research: the storms checklist. *Nature medicine*, 27(11):1885–1892, 2021.

[99] RL Morgan, SD Karam, and CJ Bradley. Ethnic disparities in imaging utilization at diagnosis of non-small cell lung cancer. *JNCI-JOURNAL OF THE NATIONAL CANCER INSTITUTE*, 112(12):1204–1212, 12 2020.

[100] Jessica Morley, Caio CV Machado, Christopher Burr, Josh Cowls, Indra Joshi, Mariarosaria Taddeo, and Luciano Floridi. The ethics of ai in health care: a mapping review. *Social Science & Medicine*, 260:113172, 2020.
[101] N Morshed and FB Zhan. Racial/ethnic, social characteristics and geographic disparities of childhood cancer late-stage diagnosis in texas, 2005 to 2014. *ANNALS OF GIS*, 27(4):329–340, 2021.
[102] Amanda J Moy, Jessica M Schwartz, RuiJun Chen, Shirin Sadri, Eugene Lucas, Kenrick D Cato, and Sarah Collins Rossetti. Measurement of clinical documentation burden among physicians and nurses using electronic health records: a scoping review. *Journal of the American Medical Informatics Association*, 28(5):998–1008, 2021.
[103] A Mukherjee, AJ Idigo, YF Ye, HW Wiener, R Paluri, LM Nabell, and S Shrestha. Geographical and racial disparities in head and neck cancer diagnosis in south-eastern united states: Using real-world electronic medical records data. *HEALTH EQUITY*, 4(1):43–51, 2020.
[104] Sendhil Mullainathan and Ziad Obermeyer. Diagnosing physician error: A machine learning approach to low-value health care. *The Quarterly Journal of Economics*, 137(2):679–727, 2022.
[105] Keisuke Nakagawa, Lama Moukheiber, Leo A Celi, Malhar Patel, Faisal Mahmood, Dibson Gondim, Michael Hogarth, and Richard Levenson. Ai in pathology: what could possibly go wrong? In *Seminars in Diagnostic Pathology*, volume 40, pages 100–108. Elsevier, 2023.
[106] Sophia R Newcomer, Stan Xu, Martin Kulldorff, Matthew F Daley, Bruce Fireman, and Jason M Glanz. A primer on quantitative bias analysis with positive predictive values in research using electronic health data. *Journal of the American Medical Informatics Association*, 26(12):1664–1674, 2019.
[107] C Niederwanger, T Varga, T Hell, D Stuerzel, J Prem, M Gassner, F Rickmann, C Schoner, D Hainz, G Cortina, B Hetzer, B Treml, and M Bachler. Comparison of pediatric scoring systems for mortality in septic patients and the impact of missing information on their predictive power: a retrospective analysis. *PEERJ*, 8, 10 2020.
[108] Ziad Obermeyer, Brian Powers, Christine Vogeli, and Sendhil Mullainathan. Dissecting racial bias in an algorithm used to manage the health of populations. *Science*, 366(6464):447–453, 2019.
[109] OE Okunlola, MS Lipnick, PB Batchelder, M Bernstein, JR Feiner, and PE Bickler. Pulse oximeter performance, racial inequity, and the work ahead. *RESPIRATORY CARE*, 67(2):252–257, 2 2022.
[110] J Omorodion, L Dowsett, RD Clark, J Fraser, A Abu-El-Haija, A Strong, MH Wojcik, AS Bryant, and NB Gold. Delayed diagnosis and racial bias in children with genetic conditions. *AMERICAN JOURNAL OF MEDICAL GENETICS PART A*, 188(4):1118–1123, 4 2022.
[111] Alan G. Palestine, Pauline T. Merrill, Sophia M. Saleem, Douglas A. Jabs, and Jennifer E. Thorne. Assessing the precision of icd-10 codes for uveitis in 2 electronic health record systems. *JAMA ophthalmology*, 136(10):1186–1190, 10 2018. PMID: 30054618 PMCID: PMC6583860.
[112] Parita Patel, Charles Muller, and Sonali Paul. Racial disparities in nonalcoholic fatty liver disease clinical trial enrollment: A systematic review and meta-analysis. *World Journal of Hepatology*, 12(8):506–518, 8 2020. PMID: 32952877 PMCID: PMC7475777.
[113] Louis A. Penner, John F. Dovidio, Richard Gonzalez, Terrance L. Albrecht, Robert Chapman, Tanina Foster, Felicity W. K. Harper, Nao Hagiwara, Lauren M. Hamel, Anthony F. Shields, Shirish Gadgeel, Michael S. Simon, Jennifer J. Griggs, and Susan Eggly. The effects of oncologist implicit racial bias in racially discordant oncology interactions. *Journal of clinical oncology : official journal of the American Society of Clinical Oncology*, 34(24):2874–2880, 8 2016. PMID: 27325865 PMCID: PMC5012663.
[114] Oriel Perets and Nadav Rappoport. Ensemble synthetic ehr generation for increasing subpopulation model's performance. *arXiv preprint arXiv:2305.16363*, 2023.
[115] Susan E Puumala, Katherine M Burgess, Anupam B Kharbanda, Heather G Zook, Dorothy M Castille, Wyatt J Pickner, and Nathaniel R Payne. The role of bias by emergency department providers in care for american indian children. *Medical care*, 54(6):562–569, 2016.
[116] K Reinard, DR Nerenz, A Basheer, R Tahir, T Jelsema, L Schultz, G Malik, EL Air, and JM Schwalb. Racial disparities in the diagnosis and management of trigeminal neuralgia. *JOURNAL OF NEUROSURGERY*, 126(2):368–374, 2 2017.
[117] David Robertson and Gordon H Williams. *Clinical and translational science: principles of human research*. Academic Press, 2009.
[118] CA Samuel-Ryals, OM Mbah, SP Hinton, SH Cross, BB Reeve, and SB Dusetzina. Evaluating the contribution of patient-provider communication and cancer diagnosis to racial disparities in end-of-life care among medicare beneficiaries. *JOURNAL OF GENERAL INTERNAL MEDICINE*, 36(11):3311–3320, 11 2021.
[119] O Sartor, MJ Morris, and BJ Kraus. Racial bias in pulse oximetry measurement (vol 383, pg 2477, 2020). *NEW ENGLAND JOURNAL OF MEDICINE*, 385(26):2496–2496, 12 2021.
[120] DM Schiff, T Nielsen, BB Hoeppner, M Terplan, H Hansen, D Bernson, H Diop, M Bharel, EE Krans, S Selk, JF Kelly, TE Wilens, and EM Taveras. Assessment of racial and ethnic disparities in the use of medication to treat opioid use disorder among pregnant women in massachusetts. *JAMA NETWORK OPEN*, 3(5), 5 2020.
[121] Andi Shahu, Jeph Herrin, Sanket S. Dhruva, Nihar R. Desai, Barry R. Davis, Harlan M. Krumholz, and Erica S. Spatz. Disparities in socioeconomic context and association with blood pressure control and cardiovascular outcomes in allhat. *Journal of the American Heart Association*, 8(15):e012277, 8 2019. PMID: 31362591 PMCID: PMC6761647.
[122] E Shimron, JI Tamir, K Wang, and M Lustig. Implicit data crimes: Machine learning bias arising from misuse of public data. *PROCEEDINGS OF THE NATIONAL ACADEMY OF SCIENCES OF THE UNITED STATES OF AMERICA*, 119(13), 3 2022.

[123] Haytham Siala and Yichuan Wang. Shifting artificial intelligence to be responsible in healthcare: A systematic review. *Social Science & Medicine*, 296:114782, 2022.
[124] Omar Sims, David Pollio, Barry Hong, and Carol North. Racial disparities in hepatitis c treatment eligibility. *Annals of hepatology*, 16(4):530–537, 8 2017. publisher-place: Mexico PMID: 28611273.
[125] Sachil Singh. Racial biases in healthcare: Examining the contributions of point of care tools and unintended practitioner bias to patient treatment and diagnosis. *Health*, 27(5):829–846, 2023.
[126] Emily A. Slopnick, Simon P. Kim, Jonathan E. Kiechle, Christopher M. Gonzalez, Hui Zhu, and Robert Abouassaly. Racial disparities differ for african americans and hispanics in the diagnosis and treatment of penile cancer. *Urology*, 96:22–28, 10 2016. publisher-place: United States PMID: 27402373.
[127] "Statista". Healthcare data storage constraints globally 2020 forecast | statista. [Online; accessed 2023-06-21].
[128] AE Stenzel, RA Fenstermaker, LM Wiltsie, and KB Moysich. Disparities among racial/ethnic groups of patients diagnosed with ependymoma: analyses from the surveillance, epidemiology and end results (seer) registry. *JOURNAL OF NEURO-ONCOLOGY*, 144(1):43–51, 8 2019.
[129] MW Sullivan, FT Camacho, AM Mills, and SC Modesitt. Missing information in statewide and national cancer databases: Correlation with health risk factors, geographic disparities, and outcomes. *GYNECOLOGIC ONCOLOGY*, 152(1):119–126, 1 2019.
[130] Martin J. Tobin and Amal Jubran. Pulse oximetry, racial bias and statistical bias. *Annals of intensive care*, 12(1):2, 1 2022. PMID: 34981267 PMCID: PMC8723900.
[131] Nenad Tomašev, Xavier Glorot, Jack W. Rae, Michal Zielinski, Harry Askham, Andre Saraiva, Anne Mottram, Clemens Meyer, Suman Ravuri, Ivan Protsyuk, Alistair Connell, Cían O. Hughes, Alan Karthikesalingam, Julien Cornebise, Hugh Montgomery, Geraint Rees, Chris Laing, Clifton R. Baker, Kelly Peterson, Ruth Reeves, Demis Hassabis, Dominic King, Mustafa Suleyman, Trevor Back, Christopher Nielson, Joseph R. Ledsam, and Shakir Mohamed. A clinically applicable approach to continuous prediction of future acute kidney injury. *Nature*, 572(7767):116–119, 8 2019. number: 7767 publisher: Nature Publishing Group.
[132] Andrea C Tricco, Erin Lillie, Wasifa Zarin, Kelly K O'Brien, Heather Colquhoun, Danielle Levac, David Moher, Micah DJ Peters, Tanya Horsley, Laura Weeks, et al. Prisma extension for scoping reviews (prisma-scr): checklist and explanation. *Annals of internal medicine*, 169(7):467–473, 2018.
[133] Jessica W. Tsai and Jennifer C. Kesselheim. Addressing implicit bias in pediatric hematology-oncology. *Pediatric blood cancer*, 67(5):e28204, 5 2020. publisher-place: United States PMID: 32159300.
[134] E Tsoy, RE Kiekhofer, EL Guterman, BL Tee, CC Windon, KA Dorsman, SC Lanata, GD Rabinovici, BL Miller, AJH Kind, and KL Possin. Assessment of racial/ethnic disparities in timeliness and comprehensiveness of dementia diagnosis in california. *JAMA NEUROLOGY*, 78(6):657–665, 6 2021.
[135] S Udoetuk, D Dongarwar, and HM Salihu. Racial and gender disparities in diagnosis of malingering in clinical settings. *JOURNAL OF RACIAL AND ETHNIC HEALTH DISPARITIES*, 7(6):1117–1123, 12 2020.
[136] Valeria S. M. Valbuena, Ryan P. Barbaro, Dru Claar, Thomas S. Valley, Robert P. Dickson, Steven E. Gay, Michael W. Sjoding, and Theodore J. Iwashyna. Racial bias in pulse oximetry measurement among patients about to undergo extracorporeal membrane oxygenation in 2019-2020: A retrospective cohort study. *Chest*, 161(4):971–978, 4 2022. PMID: 34592317 PMCID: PMC9005857.
[137] Michelle Van Ryn and Jane Burke. The effect of patient race and socio-economic status on physicians' perceptions of patients. *Social science & medicine*, 50(6):813–828, 2000.
[138] Kerstin N Vokinger, Stefan Feuerriegel, and Aaron S Kesselheim. Mitigating bias in machine learning for medicine. *Communications medicine*, 1(1):25, 2021.
[139] K Wallace, H Li, CM Paulos, DN Lewin, and AV Alekseyenko. Racial disparity in survival of patients diagnosed with early-onset colorectal cancer. *COLORECTAL CANCER*, 9(3), 10 2020.
[140] F Wang, W Zheng, CE Bailey, IA Mayer, JA Pietenpol, and XO Shu. Racial/ethnic disparities in all-cause mortality among patients diagnosed with triple-negative breast cancer. *CANCER RESEARCH*, 81(4):1163–1170, 2 2021.
[141] Xiaoyan Wang, Derek S Brown, Yin Cao, Christine C Ekenga, Shenyang Guo, and Kimberly J Johnson. The impact of health insurance coverage on racial/ethnic disparities in us childhood and adolescent cancer stage at diagnosis. *Cancer*, 128(17):3196–3203, 2022.
[142] JL Wiltz. Racial and ethnic disparities in receipt of medications for treatment of covid-19 - united states, march 2020-august 2021 (vol 71, pg 96, 2022). *MMWR-MORBIDITY AND MORTALITY WEEKLY REPORT*, 71(8):325–325, 2 2022.
[143] Julie A Wolfson, Can-Lan Sun, Laura P Wyatt, Arti Hurria, and Smita Bhatia. Impact of care at comprehensive cancer centers on outcome: results from a population-based study. *Cancer*, 121(21):3885–3893, 2015.
[144] An-Kwok Ian Wong, Marie Charpignon, Han Kim, Christopher Josef, Anne AH De Hond, Jhalique Jane Fojas, Azade Tabaie, Xiaoli Liu, Eduardo Mireles-Cabodevila, Leandro Carvalho, et al. Analysis of discrepancies between pulse oximetry and arterial oxygen saturation measurements by race and ethnicity and association with organ dysfunction and mortality. *JAMA Network Open*, 4(11):e2131674–e2131674, 2021.
[145] Evan S. Wu, Jong Y. Park, Joseph A. Zeitouni, Carmen R. Gomez, Isildinha M. Reis, Wei Zhao, Deukwoo Kwon, Eunkyung Lee, Omar L. Nelson, Hui-Yi Lin, Elizabeth J. Franzmann, Jason Savell, Thomas V. McCaffrey, W. Jarrard Goodwin, and Jennifer J. Hu. Effect of

actionable somatic mutations on racial/ethnic disparities in head and neck cancer prognosis. *Head neck*, 38(8):1234–1241, 8 2016. publisher-place: United States PMID: 27028310.

[146] GY Wu, J Wu, XB Pan, B Liu, ZC Yao, Y Guo, XL Shi, and YT Ding. Racial disparities in alpha-fetoprotein testing and alpha-fetoprotein status associated with the diagnosis and outcome of hepatocellular carcinoma patients. *CANCER MEDICINE*, 8(15):6614–6623, 11 2019.

[147] Haifeng Xu, Jianfei Pang, Weiliang Zhang, Xuemeng Li, Mei Li, and Dongsheng Zhao. Predicting recurrence for patients with ischemic cerebrovascular events based on process discovery and transfer learning. *IEEE Journal of Biomedical and Health Informatics*, 25(7):2445–2453, 7 2021. event-title: IEEE Journal of Biomedical and Health Informatics.

[148] Kun-Hsing Yu, Andrew L Beam, and Isaac S Kohane. Artificial intelligence in healthcare. *Nature biomedical engineering*, 2(10):719–731, 2018.

[149] Carolyn W Zhu, Judith Neugroschl, Lisa L Barnes, and Mary Sano. Racial/ethnic disparities in initiation and persistent use of anti-dementia medications. *Alzheimer's & Dementia*, 18(12):2582–2592, 2022.

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