"Designing Fairness: A Systematic Review of Bias Detection and Mitigation in EHR-Based Artificial Intelligence"

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ABSTRACT

Objectives: This research explores methods for addressing various forms of bias in artificial intelligence models developed with electronic health record data. Healthcare might be revolutionised by the combination of artificial intelligence and electronic health data, but it is essential to tackle bias in AI to prevent the worsening of healthcare inequalities.

Materials and Methods: Following the recommendations for reporting systematic reviews and meta-analyses, we carried out a systematic review. We examined publications through IEEE, WoS & PubMed that were from January 1, 2010, until December 17, 2023.Paper evaluated metrics for bias assessment, identified important biases, and described methods for identifying and reducing bias throughout the creation of the AI model.

Results: Twenty of the 450 publications that were retrieved satisfied our requirements, identifying six main categories of bias: temporal, measurement, confounding, implicit, algorithmic, and selection. None of the AI models have been used in actual healthcare environments; they were mostly created for predicting purposes. Five research focused on using fairness indicators such as statistical parity, equal opportunity, and predictive equity to discover algorithmic and subconscious biases. Targeting implicit and selective biases in particular, fifteen research offered methods for reducing biases. These tactics mostly concerned data collecting and preprocessing methods like resampling and reweighting, and they were assessed using both performance and fairness indicators.

Discussion: In addition to highlighting the urgent need for both standardised and thorough reporting of the methodology as well as rigorous real-world testing and assessment, this research focuses on creating methods to remove bias from AI models that use electronic health records. These metrics are crucial for assessing the usefulness of models and developing moral AI that guarantees justice or integrity in health.

Keywords: *AI, Bias, EHR*

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INTRODUCTION

Artificial intelligence's quick development in the medical field has significantly altered clinical decision-making and medical research, especially by using large amounts of actual digital medical record data. Over the past decade, electronic health records became complex in artificial intelligence research.[1] In contrast to AI applications designed to enhance the larger healthcare system, including medication research, public health surveillance, and hospital operations, individual patient records and clinical decision-making processes are becoming more closely associated with AI models derived from electronic health record data. Activities involve assessing outcomes, predicting the course of a disease, and identifying risks[2-3], Particularly appropriate for developing based on data artificial intelligence (AI) systems for predicting outcomes are electronic health records, since they contain a variety of patient data, such as demographics, lab results, diagnoses, and treatments.[4-5]

Integrating artificial intelligence with electronic health record data is vital for advancing clinical decision-making and medical research, but it encounters obstacles due to biases in both AI models and EHR data. These obstacles include inconsistent documentation, variable data quality, and inaccurate models.[6-7] These errors can cause different performance across patient subgroups, potentially escalating healthcare disparities. They typically take the form of analytical errors and skewed out results, which are frequently the result of disproportionate dataset representation.[8-9] At several phases of the model development lifecycle, biases may surface,[10-11] For these tactics to be applied effectively and fairly, they must be customised to the particulars of AI models and EHR data. Despite the fact that several scoping assessments have been carried out to comprehend bias in more general medical AI applications, a targeted examination of AI models created utilising EHR data is noticeably lacking.[12-15]

OBJECTIVE

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The goal of this study is to thoroughly examine and compile the body of research constructed using electronic health record information, with an emphasis to methods for identifying, evaluating, and mitigating the main types of bias at every stage of the model building process.

MATERIALS AND METHODS

Sources of data & searches

The Research had registered in PROSPERO database (registration number: CRD420251034022). As shown in Figure 1, This research adhered to the 2021 guidelines for reporting systematic reviews and meta-analyses. To identify publications from January 1, 2010, to December 17, 2023, we carried out methodical scans in 3 important data bases: the IEEE Xplore Digital Library, WoS, and PubMed/MEDLINE. Table 1 lists the search terms that are used for each database. The PICO Framework is:

P (Population/Problem):

AI models created with EHR data, especially those prone to showing bias.

I (Intervention):

Strategies for identifying and reducing bias, including methods used during the stages of preparing data, processing data, and after processing data in the development of AI models.

C (Comparison):

In many studies, the comparison is between biased vs. unbiased models, or models with vs. without mitigation techniques. However, since it's a review of methodologies, a direct comparison group is not always specified.

O (Outcome):

Enhanced fairness, increased accuracy within different subgroups, and decreased algorithmic bias.

Inclusion and exclusion criteria

Articles were selected based on the following criteria: (1) written in English, (2) containing full text and metadata (authors, title, and year of publication), (3) from 01.01.10, until 17.12.23 (4) focusing an AI model using Electronic Health Record data and (5) evaluating bias, specifically detailing its impact on healthcare disparities and strategies for managing bias.

Categorization of bias types

A systematic two-step procedure was used to categorise the different forms of bias. In order to represent the state of knowledge on biases in AI research, we looked at the biases mentioned in the chosen studies. This preliminary investigation gave a clear picture of the main problems in the sector. Next, we broadened our focus by incorporating knowledge from the larger body of research on healthcare AI, by combining well-known bias risk assessment methods like ROBINS-I,[16] ROBINS-E,[17] and PROBAST[18] with pertinent review papers like Mehrabi et al.[19] that categorised possible biases, our findings were further improved. By integrating these approaches, we were able to fully comprehend the bias landscape in this field by defining and classifying the primary forms of bias.

Workflow construction and bias analysis

We developed a framework to classify and analyse approaches to tackling bias in AI model development, which is shown in Figure 2. This framework outlines the main possible biases that might occur throughout the three crucial phases of gathering and preparing data, testing and training models, and deploying models (as looked at in the step above). We analysed focused mitigation strategies and identified certain forms of bias for each stage. These techniques are categorized into procedures for data preparation, model training, and model evaluation, corresponding to different stages of AI model development.[20-21]

RESULTS

This part provides our detailed analysis of the examined studies after outlining the main categories of bias found in our literature study, defining and explaining each one. Six main categories of bias that might exist in the creation of AI models based on EHRs were discovered by us:

Implicit bias: also called as prejudice bias, occurs unintentionally & spontaneously.[22]

Selection bias: When data preparation fails to appropriately randomise people, groups, or data utilised for analysis, bias of this type results. Other names for it include population bias and sample bias.[23-24]

Measurement bias: This bias typically appears during a study's data collecting phase and is frequently brought on by inaccurate or incomplete data entry made by physicians or clinical equipment.[25]

Confounding bias is a systematic distortion caused by unrelated factors between an exposure and a health result. It is sometimes referred to as association bias.[24]

When social prejudices and views are consistently reflected, it is known as *temporal bias*.[26]

Results of the screening and selection of articles

The procedure for choosing and screening articles is shown in Figure 1.
From the initial 450 items identified, 92 were duplicates, resulting in 358 articles. After 117 articles were subjected to full-text assessment, 97 were further eliminated because they used non-EHR data (n = 16), lacked explicit techniques to identify or reduce bias in AI models (n = 66), and did not assess the effect of bias directly (n = 14). Before we completed this review, one publication was withdrawn. In the end, the final analysis had 20 articles.

Research assignments and measures for evaluating bias

We classified the primary duties of each study's AI models, as indicated in Table 1, in order to comprehend how bias may have affected AI applications. As shown in Tables 2, the studies that were part of this evaluation used a wide range of measures to evaluate bias, with definitions provided in Table 3.

Features of Identifying and reducing prejudice

Out of the 20 papers in this evaluation, 11 (55%) dealt with unconscious bias, six (30%) with selection bias, six (30%) with algorithmic bias, One with measurement bi, one with temporal bi, and one with confounding bi. Six (30%) of the research looked at two forms of bias, whereas the other studies only looked at one.

Five (25%) of the 20-research included in this study only identified and explained, as shown in Table 2. The remaining 15 (75%) made an effort to lessen prejudices. Twelve out of fifteen (80%) of these mitigation strategies indicated better performance following bias reduction. On the other hand, one study (6.7%) discovered performance fluctuation depending on the assessment metrics employed, while two studies (13.3%) noted that performance remained essentially constant following bias reduction.

The phases of developing an AI application based on EHRs, reduction strategies are shown in Figure 2. Table 3 provided a description of each study's methodology when matching the included articles to each stage. Eleven research (73.3%) used bias mitigation techniques, such as resampling, reweighting, transformation, relabelling, and blinding, at the preprocessing stage. Three research (20%) created in-processing strategies such as reweighting and transfer learning.

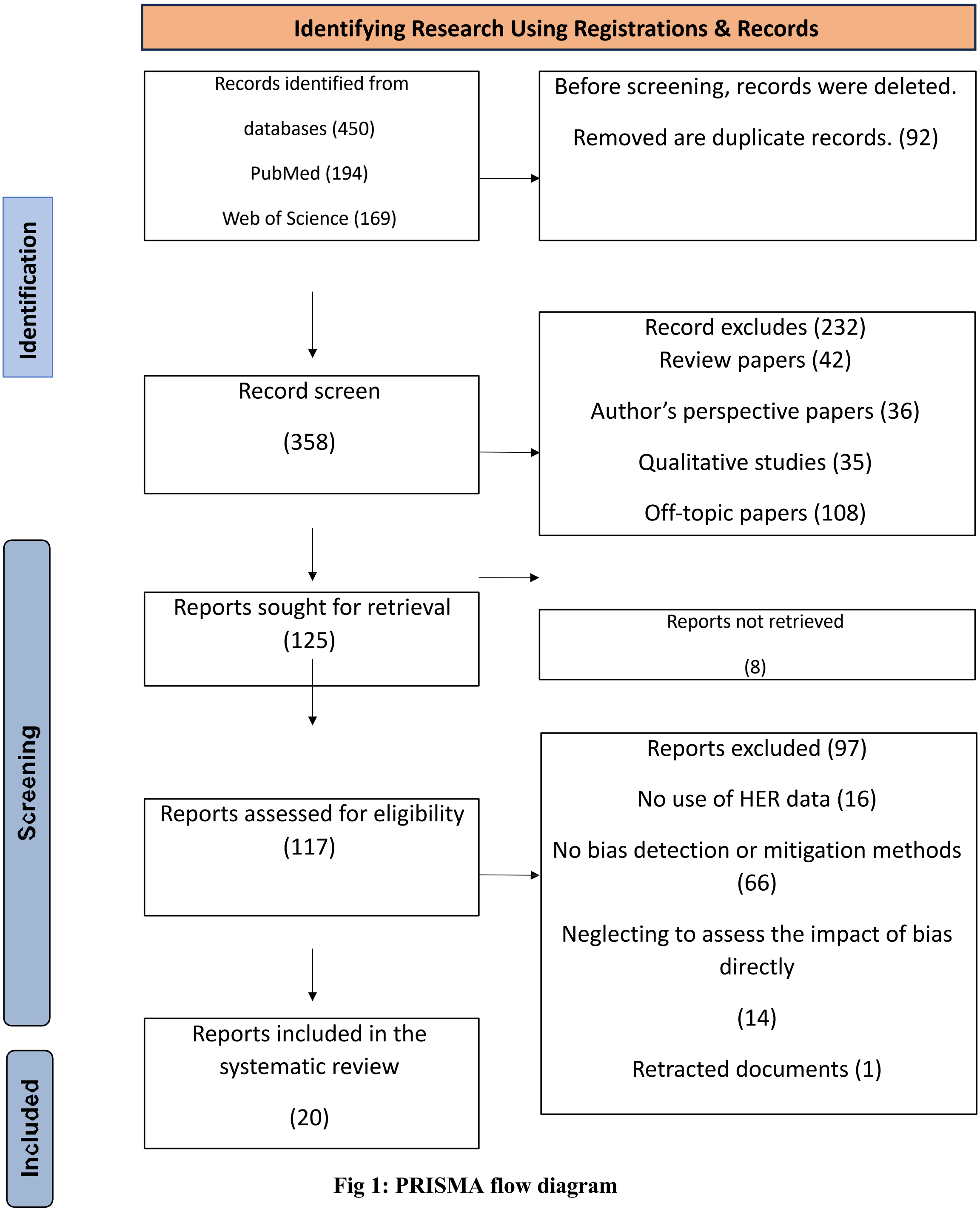

Fig 1: PRISMA flow diagram

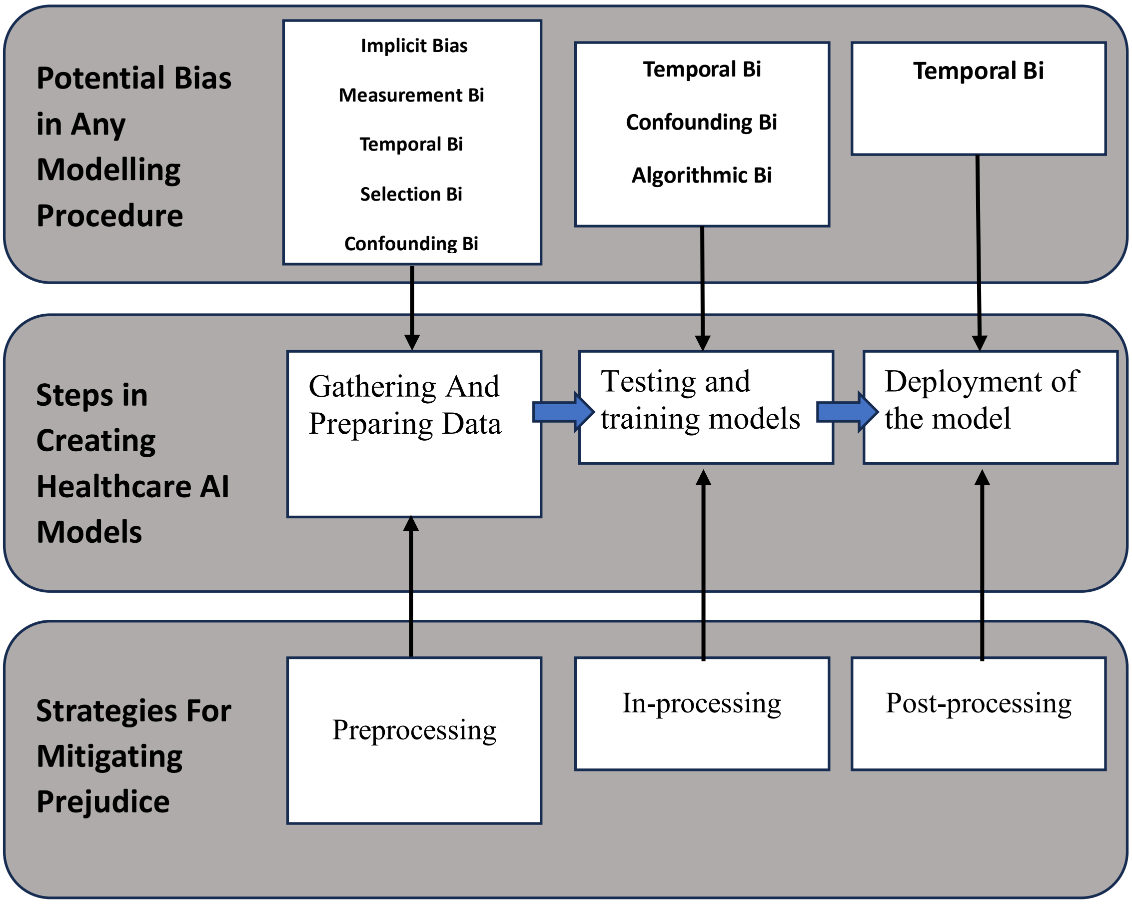

Fig 2: Process for managing bias to the creation of artificial intelligence system

Table 1. Overview of the subjects and data sources covered in the examined articles

Article	AI Model Objective	Data Source	Sample Size
Karlsson et al35	Predicting adverse drug reactions	Stockholm Electronic Patient Record Corpus, Sweden	N/A
Hee et al5	Forecasting mortality for 9 common illnesses	MIMIC-III, MA, USA	40,000
Zhu et al36	Estimating hospital readmission likelihood	Over 10 South Florida regional hospitals, FL, USA	92,827
Huda et al37	Classifying health status or capability	Prospective pilgrims in Purworejo, Indonesia	2,425
Allen et al38	Forecasting mortality	MIMIC-III, MA, USA	28,460
Khoshnevisan et al39	Early detection of septic shock	Christiana Care Health System; Mayo Clinic, USA	61,848

Article	AI Model Objective	Data Source	Sample Size
Juhn et al40	Predicting asthma exacerbation risk	Mayo Clinic, USA	555
Wolk et al41	Predicting influenza complication risk	Geisinger, PA, USA	604
Getz et al42	Imputing missing data in metastatic urothelial carcinoma patients' records	Flatiron Health database, USA	38,938
Meng et al43	Forecasting mortality for ICU patients	MIMIC-IV, MA, USA	43,005
Wang et al44	Forecasting mortality for sepsis patients	MIMIC-III; STARR, USA	11,719
Roosli et al45	Predicting in-hospital mortality risk	MIMIC-IV; eICU, USA	18,094
Li et al47	Predicting glaucoma disease progression	Department of Ophthalmology in NYU Langone Health, NY, USA	160
Lee et al4	Predicting cardiovascular disease risk	Vanderbilt University Medical Center, TN, USA	360
Li et al48	Predicting acute postoperative pain levels	University of Florida Health System/Shands Hospital, FL, USA	785
Davoudi et al49	Ranking coronary heart disease risks	MIMIC-III; eICU, USA	10,949
Cui et al50	Imputing missing temporal data in health records	MIMIC-III; eICU, USA	14,263
Yin et al51	Predicting ICU readmission	MIMIC-III, MA, USA	21,139
Raza and Bashir52	Predicting post-liver transplant risk factors	Organ Procurement and Transplantation Network, USA	13,112

Table 2. Summary of papers on methods for identifying bias

Articles	Types of Bias	Evaluation Metric	Methods of Bias Detection	Summary of Bias Detection
Juhn et al40	Unconscious bi	Predictive equity, identical chances, identical probabilities, and precision	After principal component factor analysis, to build HOUSES, four real estate parameters of a single dwelling group are used, a novel feature that measures SES at the individual level.	Compared to children with greater SES, children with asthma who have lower SES had higher mistake rates and more missing information that

Articles	Types of Bias	Evaluation Metric	Methods of Bias Detection	Summary of Bias Detection
				is pertinent to asthma therapy.
Roosli et al45	Unconscious bi; algorithmic bi	Large-scale calibration and statistical parity	The calibration and statistics symmetry are tested using three steps of model validation, which are based on AUROC and AUPRC, respectively. The AUROC differences between the entire cohort and subpopulations are investigated using permutation testing.	Minority class cases are difficult for the prediction model to properly and effectively categorise.
Wang et al44	Unconscious bi; algorithmic bi	Symmetry in statistics	Models' AUROC and feature significance are compared for each group and overall.	In terms of death estimation, minority economic and ethnic groups do poorly.
Meng et al43	Unconscious b; algorithmic bi	Symmetry in statistics	Following training on the entire set of data, confusion measures are computed and contrasted for every subgroup.	There are variations in performance between groups, and models depend on many ethnic characteristics.
Raza et al52	Unconscious bi	Predictive fairness, proportion equality, equal opportunity, and false negative rate parity	Following training on the entire set of data, confusion measures are computed and contrasted for every subgroup.	Based on four fairness criteria, the readmission forecast shows differences between various socioeconomic groups.

Table 3. Assessment measures discussed in the examined articles

Periods	Interpretation
Performance metric	
AUROC	Calculating the area under the probability curve that displays the TPR versus FPR at different Thresholds in order to assess overall performance.
Precision	Calculating the percentage of outcomes that were accurately anticipated.
F1-scores	Measuring the PPV and TPR sensitivity in the same way as the TPR, which calculates the likelihood that a sick person will test positive.
Selectivity	Similar to the model's FNR.
MAE	Calculating the mean of the absolute deviation between the actual and anticipated values.
Fairness metric Calibration-based metrics	Calculating the variation between each group's average anticipated and observed risk.

Periods	Interpretation
Performance metric	
Calibration-in--large	
Score-based metric Percent bi	Calculating the average likelihood that the projected values would differ from the actual ones in size.
xAUC	The model's ability to differentiate between good instances in group A and negative ones in group B, and vice versa, using a cross-group assessment based on AUC.
Confusion Matrix-based metrics Equal odd	Measuring the percentage of actual negatives that are projected to be positive, or FPR, as well as TPR between groups.
Similar Chances	Representing the equal TPR across groups.
Fairness of prediction	Also referred to as predictive parity, this metric calculates the variation in FPR between groups.
Symmetry of ratio	Determining if the representation of each group is commensurate with its demographic share.
False negative rate parity	Calculating the FNR for various groupings.
Parity-based metrics Statistical parity	Also referred to as demographic parity or differential effect, this metric quantifies how different groups' odds of achieving a favourable outcome are.

DISCUSSION

AI's unparalleled capacity to use EHR data for a variety of purposes, including risk assessment, illness progression prediction, and mortality prediction, has made its expanding importance in healthcare especially clear.[27] On the other side, AI models could contain biases and might worsen healthcare inequities if they are not addressed. In order to lessen healthcare inequities, it is important to carefully examine any potential biases generated by AI models47 and gauge how equitable AI approaches are.[28-30]

Principal forms of bias in AI models that use data from EHRs

At least one research has addressed each of the six categories of prejudice in this review, with the majority concentrating on implicit and selective biases. The unique effects of confounding and algorithmic biases on health inequalities have not been fully investigated when applied to EHR data. [31-33]

Assessments of fairness and bias

There is a methodological discrepancy in the bias evaluation techniques used in the examined research; around half use fairness measures to evaluate group biases. The others depended on broad performance indicators like specificity, sensitivity, and accuracy, which are helpful for assessing the overall performance of the model but could miss small but important differences across groups. This carelessness may obscure possible biases and obscure the varying effects of AI models on various patient groups.[34]

Using strategies for bias mitigation

Preprocessing, in-processing, and postprocessing are the three phases into which bias reduction strategies are divided in this review. Commonly address is preprocessing. These techniques may be easily included into clinical workflows and provide observable early-stage bias reduction. By changing how the learning info is distributed, two crucial techniques in this group—resampling and reweighting—successfully resolve any disparity in community. Relabelling, domain adaption, and transformation to recover missing data are further preprocessing techniques discussed in this paper. They might, however, result in data loss and be less successful in correcting feature correlations. As a result, their ability to mitigate algorithmic, temporal, and confounding bias is restricted. During model training, in-processing techniques provide flexible methods for reducing bias. To improve execution, it makes use of models that have already been trained on huge datasets. In addition to this, a number of other in-processing techniques, such as constraint optimisation to enforce fairness constraints during the learning process, have been proposed for machine learning models and may potentially be practical.

Future prospects and concerns in research

Limited research has been dedicated to this crucial subject, indicating that bias new area of study. There is an urgent need for comprehensive guidelines for applying assessment criteria in AI models developed from EHR data. Alongside traditional performance metrics, these guidelines should include fairness assessments to reduce disparities across groups. Additional investigation is required to assess their practical relevance.

The following crucial areas should be the focus of future research to enhance prejudice control in artificial intelligence for wellness:

Analysis of the integrity of the information

Pathway of identifying and reducing prejudice

Validation of AIs models

Explainable bias for AI applications

LIMITATIONS

Firstly, the inherent limitations of our keyword search strategy might have hindered the identification of potentially relevant publications, despite conducting extensive searches across three major databases Second, because the topic under evaluation is still in its infancy, the relatively small number of included papers may limit scope in research. Thirdly, there is subjectivity because the writers' interpretations and summaries in this review are predicated on their knowledge and proficiency in the specific field of research. Lastly, the impact for the models' bias mitigation techniques on clinical outcomes remains unassessed, as none of the models reviewed were evaluated in real-world clinical settings.

CONCLUSION

Research community is paying more and more attention to bias in AI models built from EHRs. In addition to highlighting recent successes, this analysis underscores the need for more thorough investigation into creating standardised, broadly applicable, and comprehensible techniques for identifying, reducing, and assessing bias in AI models. It is imperative to make sure that these tools are fair in order to reduce the possibility of bias-driven healthcare disparities. Sustained work in this field is necessary to maximise the advantages of AI in healthcare and enhance healthcare fairness.

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