Social determinants of health in the era of artificial intelligence with electronic health records: A systematic review

Anusha Bompelli[#], Department of Pharmaceutical Care & Health Systems, University of Minnesota, bompe001@umn.edu

Yanshan Wang[#], Department of AI & Informatics, Mayo Clinic, wang.yanshan@mayo.edu

Ruyuan Wan, Department of Computer Science, University of Minnesota, <u>wanxx199@umn.edu</u>

Esha Singh, Department of Computer Science, University of Minnesota, sing0640@umn.edu

Yuqi Zhou, Institute for Health Informatics and College of Pharmacy, University of Minnesota, zhou0357@umn.edu

Lin Xu, Carlson School of Business, University of Minnesota, <u>xu000532@umn.edu</u>

David Oniani, Department of Computer Science and Mathematics, Luther College, onianidavid@gmail.com

Bhavani Singh Agnikula Kshatriya, Department of Health Sciences Research, Mayo Clinic, AgnikulaKshatriya.BhavaniSingh@mayo.edu

Joyce (Joy) E. Balls-Berry, Department of Neurology, Washington University St. Louis, <u>j.balls-berry@wustl.edu</u>

Rui Zhang*, Institute for Health Informatics, Department of Pharmaceutical Care & Health Systems, University of Minnesota zhan1386@umn.edu

Equally contributed

*Corresponding author

Abstract

There is growing evidence showing the significant role of social determinant of health (SDOH) on a wide variety of health outcomes. In the era of artificial intelligence (AI), electronic health records (EHRs) have been widely used to conduct observational studies. However, how to make the best of SDOH information from EHRs is yet to be studied. In this paper, we systematically reviewed recently published papers and provided a methodology review of AI methods using the SDOH information in EHR data. A total of 1250 articles were retrieved from the literature between 2010 and 2020, and 74 papers were included in this review after abstract and full-text screening. We summarized these papers in terms of general characteristics (including publication years, venues, countries etc), SDOH types, disease areas, study outcomes, AI methods to extract SDOH from EHRs and AI methods using SDOH for healthcare outcomes. Finally, we conclude this paper with discussion on the current trends, challenges, and future directions on using SDOH from EHRs.

1. Introduction

Healthy People 2030 defined social determinants of health (SDOH) as "social determinants of health are conditions in the environments in which people are born, live, learn, work, play, worship and age that affect a wide range of health, functioning and quality of life outcomes and risks"[1]. The social determinants of health are categorized into five key categories: *economic stability*; *education access and quality*; *social and community context*; *neighborhood and built environment*; and *healthcare access and quality*[1]. As our population is becoming more diverse, there is growing evidence demonstrating the significant impact of SDOH on various healthcare outcomes such as mortality[2], [3], morbidity[4], life expectancy[3], healthcare expenditures[5], health status, functional limitations[6]. For example, a study showed that SDOH factors, including education, racial inequality, social support, and poverty, accounted for more than a third of the estimated annual deaths in the United States[6], [7].

It is not only necessary to overcome social determinants of health in order to enhance public health, but also to eliminate health inequalities that are often entrenched in social and economic inequalities. One way to address this is by integrating SDOH into the electronic health record (EHR). Increased use of EHR systems in healthcare organizations has facilitated secondary use of EHR data through artificial intelligence (AI) techniques to improve patient care outcomes[8], via clinical decision support systems, chronic disease management, and patient education. Most recently, AI methods were used to propose candidate drugs for COVIID-19[9].

SDOH information in the EHR is stored in both structured (e.g., education, salary level) and unstructured format (e.g., social history in clinical notes). Since there is no standardized framework for recording SDOH information and such information is usually incompletely recorded[10] in a structured format, it is often difficult to identify SDOH present in an unstructured format and to establish a connection between SDOH and disease or health outcomes. Approaches that leverage natural language processing (NLP) tools to extract SDOH information stored in an EHR in an unstructured format are still limited. Prior literature reviews on SDOH mainly focused on integration of SDOH into EHR[11], and impact of SDOH in risk prediction, the role of SDOH in mental health[8], availability and characteristics of SDOH in EHR[12]. None of these reviews discussed the AI methods using SDOH in EHR data. This paper

provides a systematic literature review of the SDOH factors, the relationship between SDOH and disease, and the NLP techniques used to extract SDOH information using EHR data.

2. Methods

2.1 Data sources and search strategies

This systematic literature review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. A comprehensive search of several databases from 2010 to October 15th, 2020, English language, was conducted. The databases included Ovid MEDLINE(R) and Epub Ahead of Print, In-Process & Other Non-Indexed Citations, and Daily, Ovid EMBASE, Scopus, Web of Science, the ACM Digital Library, and IEEE Xplore. The *editorial, erratum, letter, note, comment* were excluded. The search patterns used in these databases were consistent. The keywords used in the search query is shown in **Table 1**, and the query was implemented by an experienced librarian. A detailed description of the search strategies used is provided in the Supplemental Materials.

Table 1. Searching strategies used to retrieve the literature.

Category	Keywords
EHR terms	electronic health record OR electronic health records OR electronic medical records OR electronic medical record OR EHR OR EMR
SDoH terms	SDOH OR SDH OR social and behavioral determinants of health OR social determinants of health OR social determinants OR socialeconomics OR social economics OR housing OR employment OR social behavior OR Incarceration OR social support OR determinants of health OR lifestyle OR physical activity OR diet OR housing instability OR poverty OR social determinants of behavior OR food insecurity OR education OR health literacy OR health access, access to health OR transportation OR public safety OR discrimination, racism OR lack of educational attainment OR access healthcare OR avail* healthcare OR access care OR avail* care OR social depriv* OR social disadvantage OR education achieve* OR education status OR financial difficult* OR financial problem* OR income difference OR indigent OR insurance health OR insurance status OR jobless OR job insecurity OR low income OR marginalized OR occupational status OR poverty OR psychosocial depriv* OR rural health OR SES OR social environment OR social exclu* OR social factor* OR social gradient* OR social position OR social variation OR social disparity OR socioeconomic status OR socioeconomic circumst* OR socioeconomic factor* OR socioeconomic gradient* OR socioeconomic health* difference* OR socioeconomic position OR socioeconomic status socioeconomic variable OR standard living OR underinsure* health OR underprivilege* OR unemployed OR unemployment OR unisur* health OR vulnerable population* OR vulnerable group* OR vulnerable communit* OR vulnerable people OR vulnerable person* OR housing OR environmental factors OR socioeconomic OR poverty OR crowding OR overcrowding OR nutrition
AI terms	NLP OR natural language processing OR information extraction OR named entity extraction OR named entity recognition OR co-reference resolution OR relation extraction OR text mining OR artificial intelligence OR machine learning OR deep learning OR predictive modeling OR AI

2.2 Article selection

A total of 1,250 articles were retrieved from five libraries, of which 540 articles were found to be unique. The articles were then filtered manually based on the title and abstract to check whether articles are related to SDOH and AI based on the EHR data. 181 articles remained for subsequent full-text review. The inclusion criteria for the target publications are: 1) AI techniques are used, 2) the SDOH information is from the EHR data, and 3) EHR data is in English. Articles without full text were excluded. After this full-text screening process, 74 articles were selected in this systematic review. A flow chart of the article selection process is shown in **Figure 1**.

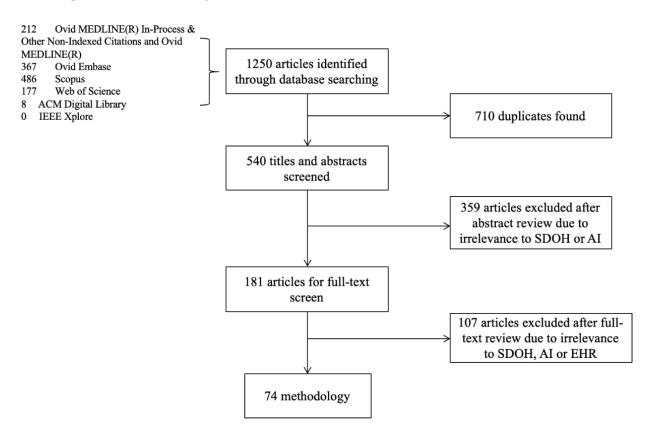


Figure 1. The flowchart of the article selection process.

3. Results

Studies on SDOH is an interdisciplinary field of healthcare, social science, and informatics,]we first analyzed the general characteristics of the 74 included studies including publication trend, journal venues. We analyzed the coverage of SDOH and disease categories and visualized their relationships in order to provide insights how the SDOH factors impact healthcare outcomes. We further summarized the data sources and sample size for accessing SDOH. In addition, we analyzed the NLP methods to extract SDOH and predictive models for predicting outcomes using SDOH variables. The details of the included articles and review analysis are further provided in the supplementary materials.

3.1. General Characteristics of the Reviewed Studies

The general characteristics of the reviewed studies are summarized in **Table 1**. All the reviewed studies are published between 2012 and 2020 (**Figure 2**) with an increasing number of publications from 2012 to 2020. The current review includes publications across 12 countries (**Figure 3**), with most of the contribution from the United States (74%) and all but 6 studies are from developed countries. Investigation of the publication venues indicates the research communities that utilize SDOH from EHRs by leveraging informatics techniques. The type of venues for conferences are determined through manually researching conference information. The venues for journals are determined through Scimago and Clarivate Analytics. All studies are generally divided into four different types: 1) Clinical (n=29); 2) Informatics (n=29); 3) Social Science (n=12) and 4) Multidiscipline (n=4).

Table 1. Characteristics and distribution of the 74 reviewed studies.

Characteristics	n	%
SDOH data source		
Structured Data	33	44
Unstructured Data	19	26
Structured Data and Unstructured Data	22	30
SDOH level		
Individual	34	46
Neighborhood	7	9
Both	33	45
Size of Data Sample		
<10,000	34	46
Between 10,000 and 100,000	17	23
>100,000	14	19
Not specified	9	12
Use of SDOH		
Predictors for predictive modeling	51	69
Disease management	17	23
Outcome of analysis	6	8
Publication Venues		
Clinical	29	39
Informatics	29	39
Social science	12	16
Multidiscipline	4	5
Informatics methods to obtain SDOH		
Predictive modeling	20	27
NLP	11	15
Statistical methods	2	3
Use 2 methods	28	38
Use all 3 methods	12	16

SDOH: Social Determinants of Health; **NLP:** Natural Language Processing.



Figure 2. Years trend of 74 reviewed studies.

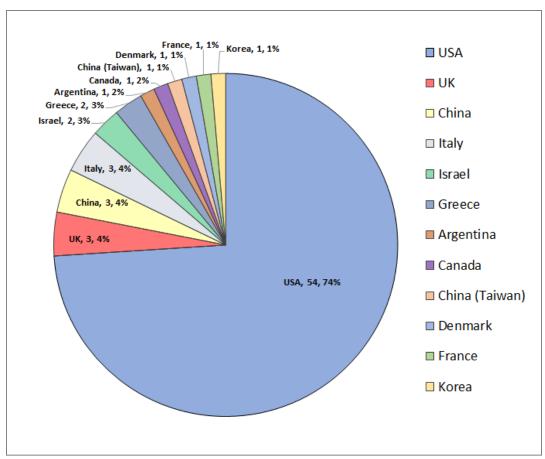


Figure 3. Summary of number of reviewed studies by country.

Overall, 44% of the reviewed studies used structured data, 26% used unstructured data and 26% used both structured and unstructured data. Electronic health records (EHR) are used in almost all studies in the

review, with other data from claims data[13]–[17], NHANES[17] and clinical trials[18]. Individual SDOH data were used in 46% of studies, neighborhood SDOH data were used in 9% of studies, and both individual and neighborhood data on SDOH were used in 45% of studies. Most of the studies (46%) have less than 10,000 data samples, 23% of studies have between 10,000 and 100,000 samples, and 198% have more than 100,000 samples.

Among all reviewed studies, the most common usage (69%) of the SDOH information is acting as predictors for health outcomes, followed by disease management (230%) and outcome of analysis (8%). The percentage of nonclinical studies (48%) is slightly lower than that of clinical studies (52%). Natural language processing (NLP) and predictive modeling are the 2 main types of AI methods used to obtain SDOH information in the reviewed studies. 27% of the total reviewed studies used only predictive modeling, 157% used only NLP and 32% used only statistical analysis. The rest of the studies used either 2 of the methods mentioned above (386%) or all 3 methods (16%).

3.2. SDOH type

There is no single standardized method for categorizing SDOH factors. For example, WHO[19] SDOH conceptual framework includes as socio-economic and political context; socio-economic position; social cohesion and social capital; and health system, while Healthy People 2030 [1] categorized SDOH factors into economic stability; education access and quality; social and community context; neighborhood and built environment; and healthcare access and quality. Since the articles we reviewed had no information on the socio-political context, we have classified the SDOH factors according to the Healthy People 2030 framework. Several studies have attempted to study the SDOH in order to determine the impact of social factors on health. The inclusion of SDOH in Table 2 was determined by coverage of SDOH in one or more publications. From the articles reviewed, the SDOH factors identified were categorized into one of the five SDOH categories. While identifying SDOH factors, few SDOH mentions from the reviewed articles have been standardized to a single SDOH factor to prevent intense granularity of SDOH factors. For example, SDOH mentions such as alcohol, tobacco, and drug abuse have been normalized to substance use/abuse SDOH factor. Most of the studies focused on more than one SDOH factor belonging to different SDOH categories.

Overall, 30% of the studies reviewed focused on SDOH factors associated with *healthcare access and quality*, 25% focused on *economic stability*, 21% focused on *social and community context*, 15% focused on *neighborhood and built environment, and* 9% focused on *education access and quality*. Widely studied SDOH factors include substance use/abuse (9%) [14], [16], [20]–[35], education (8%) [16], [21], [36]–[46], lifestyle (7%) [22], [29], [32], [43], [47]–[53], employment status (6%) [16], [20], [21], [23], [31], [36], [38], [39], [45], [46], [54], [55], socioeconomic status (6%) [29], [39], [44], [46], [56]–[63], socioeconomic factors (5%) [28], [38], [39], [46], [48], [53], [64]–[67], diet (5%) [21], [22], [26], [43], [48], [68]–[72], housing status (5%) [16], [21], [33], [35], [38], [46], [73]–[76], social support (5%) [14], [15], [35], [74], [77]–[82], physical activity (4%) [20], [31], [40], [48], [68]–[70], [78], [83], marital status (3%) [31], [36], [40], [45], [62], [84], [85], housing instability (2%) [14], [16], [45], [75], [86], environmental factors (3%) [20], [59], [63], [87], and insurance (2%) [20], [24], [38], [88]. Other significant SDOH factors include geographic location [24], [31], [44], [70], health literacy [43], [54], [88], social and behavioral determinants of health [33], [59], [73], [89], social environment [41], [63], [77], health access [21], [61], [88], living condition [20], [31], [35], and social behavior [53], [61], [82], and financial insecurity [81], [86].

 Table 2. The distribution of articles studying SDOH.

SDOH Category	SDOH	No. of Articles
Economic Stability	Employment Status	12
	Socioeconomic Status (SES)	12
	Socioeconomic Factors	10
	Housing Instability	5
	Income	2
	Financial Insecurity	2
	Vocational History	2
	Work-related Challenges	1
	Housing Insecurity	1
Education Access and Quality	Education	14
	Health Literacy	3
Healthcare Access and Quality	Substance Use/Abuse	17
	Lifestyle	11
	Diet	10
	Physical Activity	9
	Insurance	4
	Health Access	3
	Erratic Healthcare	1
	Sleep	1
Neighborhood and Built Environment	Housing Status	10
	Environmental Factors	4
	Geographic Location	4
	Living Condition	3
	Socio-environmental Neighbourhood	2
	Criminality	1
	Land Use Patterns	1
	Violence	1
	Weather	1
Social and Community Context	Social Support	10
Social and Community Context	Marital Status	7
	Social and behavioral determinants of health	4
	Social Environment	3
	Social Behaviour	3
	Psychosocial Factors	2
	Social Isolation	2
	Racial Disparities	1
	Incarceration	1

Material and Social Deprivation	1
Social Activity	1
Social Characteristics	1
Social Circumstances	1
Social Discrimination	1

3.3. Relations between SDOH and Health Outcomes

Among the 74 articles, 58 articles focused on SDOH factors associated with one or more disease conditions. From the 58 articles reviewed; the diseases investigated were grouped into one of the 12 categories (see **Table 3**). 24% of the studies focused on mental, behavioral and neurodevelopmental disorders, 16% on endocrine, nutritional and metabolic diseases, and 10% on diseases of the circulatory system. The most widely studied diseases include diabetes[45], [47], [49], [51], [66], obesity[45], [62], [68], [72], geriatric syndrome[15], [48], [78], [80], and HIV[58], [82], [89]. Other notable mentions include hypertension[45], [50], stroke[45], [74], dementia[22], [40], and cancer[32], [90]. Interesting finding is that about 6 articles[23], [27]–[29], [35], [83] studied SDOH factors related to outcome measures such as hospital readmission risk, all-cause nonelective readmission.

Table 3. Number of articles for various healthcare outcomes.

Disease/Outcome Category	No. of Articles	Disease	No. of Articl es
Certain infectious and parasitic diseases	3	HIV	3
Diseases of the circulatory system	7	Hypertension	2
		Stroke	2
		Acute myocardial infarction	1
		Cardiovascular Disease	1
		Congestive heart failure	1
Diseases of the digestive system	1	Crohn's Disease	1
Diseases of the musculoskeletal system and connective tissue	1	Gout	1
Diseases of the respiratory system	4	COVID-19	1
		Pediatric Asthma	1
		Pneumonia	1
		Seasonal influenza	1
Endocrine, nutritional and metabolic	11	Diabetes	5
diseases		Obesity	4
		Childhood obesity	1
		Familial Hypercholesterolemia	1
Injury, poisoning and certain other	4	Mild Traumatic Brain Injury (mTBI)	1

consequences of external causes		Non-fatal Suicide Attempt	1
		Post-Deployment Stress	1
		Suicide	1
Mental, Behavioral and	16	Dementia	2
Neurodevelopmental disorders		Mental Disorders	1
		AD Dementia	1
		Alzheimer's disease	1
		Attention-Deficit/Hyperactivity Disorder (ADHD)	1
		Bipolar Disorder	1
		Delirium	1
		Depression	1
		Epilepsy	1
		Major Depressive Disorder	1
		Mental Health	1
		Opioid Misuse	1
		Psychiatric Disorders that can lead to suicidal behaviors	1
		Schizophrenia-Spectrum Disorders	1
		Substance Use Disorders (SUDs)	1
Miscellaneous	10	Geriatric Syndrome	4
		Multiple Diseases	2
		Allograft survival	1
		Chronic Diseases	1
		Postnatal Growth	1
		Total Knee Arthroplasty (TKA)	1
Neoplasms	3	Cancer	2
		Prostate Cancer	1
Outcome Measures	6	Hospital readmission risk	2
		30-day all-cause nonelective readmission	1
		3-Day Postdischarge Readmissions	1
		First emergency admission prediction	1
		risk of 30 day readmission	1
Pregnancy, childbirth and the puerperium	1	Gestational diabetes mellitus (GDM)	1

SDOH reflects social, physical, economic, environmental influences that can or cannot be regulated by the person but have a major effect on the wellbeing of the individual. The SDOH factors can act either as risk factors or intervention factors and can influence the burden of disease. There is very little research on the relationship between the variables of SDOH and the disease. It is necessary to know the factors that influence the disease and to better understand the relationship, we have tried to draw attention to the diseases

listed in the articles and their respective SDOH factors. **Figure 4** shows that the top 10 SDOH factors include education, substance use/abuse, socioeconomic status (SES), diet, lifestyle, social support, employment status, socioeconomic factors, marital status, and physical activity. Whereas the top 5 diseases include obesity, geriatric syndrome, diabetes, HIV and stroke.

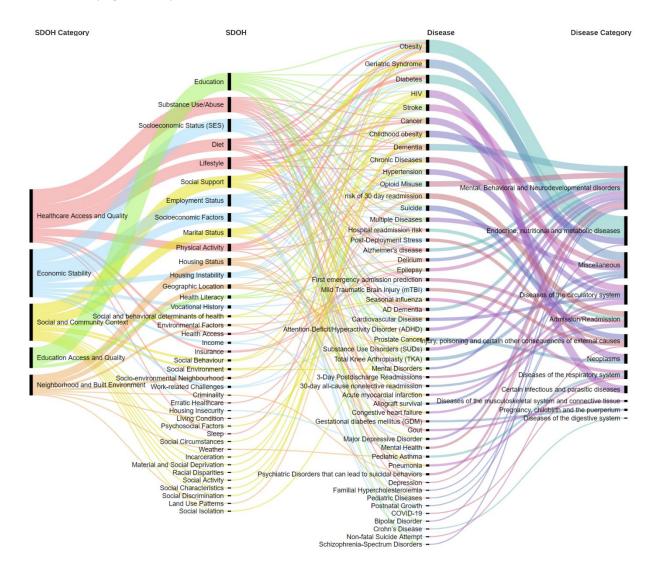


Figure 4. Overview of the relationship schema between SDOH and disease.

Healthcare Access and Quality. The SDOH factors such as substance use/abuse, diet, lifestyle and physical activity were mainly studied in endocrine, nutritional and metabolic diseases (diabetes and obesity) and mental, behavioral and neurodevelopmental disorders (Alzheimer's disease, dementia, mental disorders, delirium and depression). Two studies showed data integration through the semantic ETL service[68] and the MOSAIC dashboard system [47], using SDOH factors such as lifestyle, physical activity and diet could improve the management of obesity and diabetes. Hosomura et al. shown that educating patients with lifestyle interventions has been associated with improved glycemic control in diabetes patients [49], whereas Zhou et al. analyzed published lifestyle exposures and related intervention strategies for AD patients [22].

Economic Stability. The association between SDOH factors such as socioeconomic factors, employment status, SES and mental, behavioral and neurodevelopmental disorders (opioid misuse, ADHD, SUDs) and Injury, poisoning and certain other consequences of external causes (suicide, post-deployment stress) was widely studied. Zhang et al. and Afshar et al. studied the impact of low socioeconomic status and socioeconomic distress in individuals with at-risk comorbid SUDs [44] and opioid misuse [46] respectively. Zheng et al developed an early-warning system to identify patients at risk of suicide attempts[39] and few studies stated that the predictors like SES[60], socioeconomic factors [64] can be used to predict suicide risk.

Education Access and Quality. Education factor was critically analyzed in the mental, behavioral and neurodevelopmental disorders category (ADHD, bipolar disorder, dementia, mental disorders, opioid misuse, schizophrenia, substance use disorders (SUDs)). Education level in association with other factors like employment status, income found to have a significant correlation to suicidal behavior in patients with mental illness [39]. Senior et al developed OxMIS tool to predict suicide in patients with severe mental illness using SDOH factors such as highest education, substance abuse [42].

Social and Community Context. Although about 15 SDOH factors belong to this category, factors such as social support and marital status have been widely studied. Poor social support has shown to have an impact on hospital readmission [14], in patients with HIV [82] or Dementia [40]. Biro et al and Ge et al, respectively, studied the relationship between marital status and conditions such as obesity [62], suicidal ideation specific to major depressive disorder [85].

Neighborhood and Built Environment. Housing status and geographic location were focused in the mental, behavioral and neurodevelopmental disorders category (delirium, ADHD, opioid misuse, substance use disorders (SUDs)) and disease of the circulatory system (congestive health failure, acute myocardial infarction, stroke). Davoudi et al. and Nau et al. studied how geographic location serves as a surrogate of socioeconomic characteristics of the neighborhood, that have been shown to be associated with multiple diseases and health behaviors [24], and high mortality [70].

Among the individual diseases, Obesity has been extensively studied, and the most researched factors include diet, marital status, education, employment status, housing instability, material and social deprivation, physical activity, sleep, SES and socio-environmental neighborhood. Social environment, education, financial insecurity, work-related challenges, lifestyle, and environmental factors were primary SDOH factors associated with mental disorders. Diabetes-related SDOH factors included lifestyle, socioeconomic factors, employment status, housing instability, education and marital status. Social support, physical activity, diet, lifestyle and socioeconomic factors were commonly studied with regard to geriatric syndrome. Most of the HIV-related SDOH factors fall within the *social and community context*, such as social behavior, social discrimination, incarceration, social support, and racial disparities.

3.4. NLP methods to extract SDOH from clinical texts

To extract social determinants of health, there are various methods. For structured data, using database queries and descriptive statistics is a straightforward and frequently used method. For unstructured data, NLP is widely used to extract information. Information extraction is the task of automatically extracting structured information, that is SDOH here, from unstructured or semi-structured data which is either EHR

or clinical notes of patients' visiting a clinical site. In this review, 34 papers used NLP methods to extract SDOH from clinical notes.

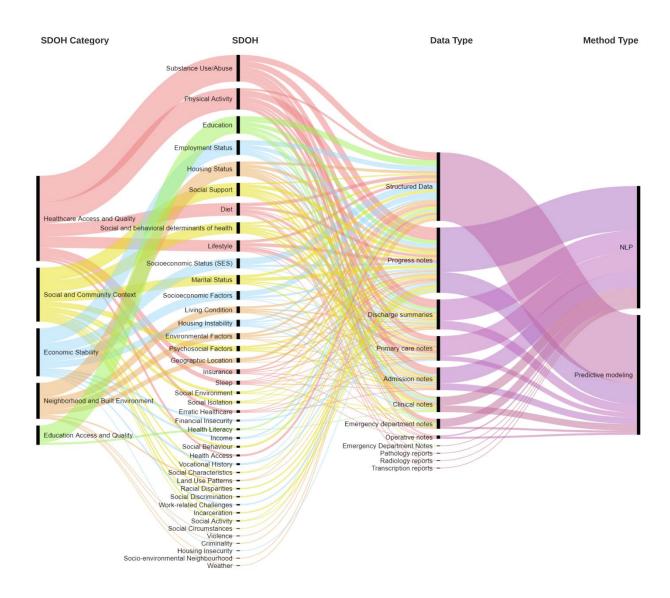


Figure 5. Overview of SDOH data source and AI methods.

NLP tools. Among these 32 articles, 15 studies [9], [11], [19], [20], [22], [25], [30]–[37] used NLP tools including Apache Ctakes [46], [52], [91], MetaMap [16], [22], [92], Moonstone [35], [74], MTERMS [14], [93], Biomedicus [31], MediClass [69], and LEO [26]. Apache cTAKES was developed on the UIMA platform and Apache openNLP toolkit and it is one of most popular NLP tools for clinical information extraction from EHR data [94]. cTAKES was used to identify subtypes of patients with opioid misuse[46], and lifestyle modification [52]. MetaMap was originally developed to map biomedical literature to UMLS Metathesaurus concepts, but later applied to clinical texts. MetaMap was used for identification of homeless patients [16] and extraction of lifestyle information [22]. The Moonstone system is an open-source rule-based clinical NLP system designed to automatically extract information from clinical notes, especially

those requiring inferencing from lower-level concepts[74]. The system was designed to extract social risk factors including housing situation, living alone, and social support [35], [74]. MTERMS [93] encodes clinical text using different terminologies and simultaneously establishes dynamic mappings between them. It was originally designed to extract medication information from clinical notes to facilitate real-time medication reconciliation, and later has been extended to support a variety of clinical applications, such as risk factor identification from physician notes [14]. BioMedICUS¹ is an open-source system, built on UIMA framework, for large-scale text analysis and processing of biomedical and clinical reports. It was used to process social history documents to identify social history topics [31]. Mediclass [95] is a knowledge-based system that can detect clinical events in both structured and unstructured EHR data. Hazlehurst et al. used the MediClass system with NLP components to identify the 5As of weight loss counseling [69]. The Leo is a framework that was first built to support scalable deployment of NLP pipelines for processing a large amount of Veteran Affairs clinical notes. It facilitates the rapid creation and deployment of Apache UIMA-Asynchronous Scaleout annotators. The Leo system employed rules to identify the plan portion of the medical records and to detect words and phrases that capture instances of behavioral modification counseling [26].

Rule-based methods. Rule-based methods were widely used (7 studies)[15], [32], [38], [76], [78], [81], [83] for extracting SDOH information from clinical records. Rules including key terms were usually manually curated by domain experts. Hollister et al. used 860 terms to extract socio-economic status related SDOH data from free texts to demonstrate the feasibility of retrieving SDOH data and linking with other health related data for genetic studies [41]. A pattern-based NLP method was used to identify additional syndromes from clinical notes including malnutrition and lack of social support [15].

Term expansion. The limitations for rule-based methods is that they are hard to capture comprehensive lexical variation in the clinical records. Thus 4 studies investigated using unsupervised learning methods to further expand terms or get word representation from unannotated clinical texts. Word embeddings is such an approach, which is a type of word representation that allows semantically similar words to have a similar presentation based on the contexts of a corpus with annotations. Shi et al. used word2vec to retrieve the vector representation for each word in the EHR data, which was then added into a deep neural network model. Lexical association is another approach, a measure determining the strength of association between two terms in a text corpus [87]. Dorr et al. used lexical association approaches to expand psychosocial terms in clinical texts, which help them to identify 90-fold increase in patients [86]. Bejan et al. implemented both lexical association and word2vec approaches to expand keywords of homelessness [73].

Topic modeling. Topic modeling is one of the unsupervised learning methods to explore latent topics in a given corpus. Three studies [40], [46], [89] used topic modeling for clinical notes. Latent Dirichlet Allocation (LDA) is a robust topic model, which learns K topics for a given corpus, where each topic is represented as a distribution of n words. Wang et al. used LDA to explore various themes (e.g., nutrition, social support) mentioned in care provider notes of dementia patients [40]. Feller et al. used both LDA and TF-IDF to identify keywords for developing a prediction model on HIV risk assessment. These keywords are related to drug use and housing instability [89].

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¹ https://github.com/nlpie/biomedicus3

Deep learning. A couple of studies developed deep learning methods [42], [80]. Chen et al. trained a deep neural network model using contextual information to identify sentences indicating the presence of a geriatric syndrome including lack of social support from clinical notes[80]. Senior et al. develop a neural network model to extract information such as the highest formal education from clinical notes as predictors for suicide in severe mental illness [42].

Corpus development. Developing corpus is vital for developing reliable NLP methods. Three studies have focused on development of annotated corpus on SDOH. Volij et al. developed an annotation standard to detect intra-social support from the electronic medical records [79]. Lybarger et al. recently using an active learning framework developed the Social History Annotation Corpus (SHAC), including 4480 social history sections for 12 SDOH characterizing the status, extent, and temporal information [20].

Conversational agent. One study designed a study to analyze the significance of employing Alexa-based intelligent agents for patient coaching. Their study has shown that intelligent agents are another highly efficient model for intervention. Furthermore, they claimed that this approach has a potential to reshape the way people apply interventions [90].

3.5. Predictive models using SDOH for healthcare outcomes

Among these studies, 54 studies used SDOH factors for predicting healthcare outcomes. Predictive modeling is a technique that uses mathematical and computational methods to predict an event or outcome in a future time point of interest. In most cases a model is chosen based on a detection theory to try to guess the probability of an outcome given a set amount of input variables. In general, these models can either make use of one or more classifiers in order to determine the probability of a set of data belonging to another set or according to the undertaken task. Below we categorized these studies based on different methods of predictive modelling techniques. Note that one study can mention multiple predictive models and thus these studies were counted for each methodology category.

Supervised Learning Methods

- 1. Regression: Regression is the mostly used approach for predicting outcomes. Fifteen studies [21], [23], [25], [30], [36], [43], [45], [53], [57], [59], [60], [63], [65], [75], [96]used various types of regression models, including logistic regression, LASSO regression, and Cox proportional models. Kim et al. used logistic regression to develop predictors for suicide using various suicidal behaviors and substance-related variables.
- 2. Random forest and decision tree: Ten studies [24], [28], [48], [50], [56], [61], [64], [70], [84], [89] used tree-based ML algorithms, including random forest and decision trees. Nau et al. utilized non-parametric machine learning methods such as Conditional Random Forest (CRF) to identify the combination of community features that are most important for the prediction of obesogenic and obesoprotective environments for children [70] whereas Agrawal et al. also used random forests along with gradient boosting methods and stacked generalization methods to attain their outcome using structured data [28]. Davoudi et al.[24], Walsh et al.[64], Grinspan et al.[88], Feller et al.[89], Erickson et al.[16], all make use of random forest variants.

- 3. Neural Networks: Eight studies utilized neural networks[27], [39], [44], [59], [60], [65], [87], [97]. Shi et al. [87] implements bidirectional RNN to predict pediatric diagnosis whereas Vrbaški et al. [97] develop predictors for lipid profile prediction. Both methods use a combination of structured and structured data with various natural language preprocessing steps. Xue et al. [45]utilized an RNN-based time-aware architecture to predict obesity status. An ensemble model with cross-sectional random forest (RF) model, a longitudinal recurrent neural network (RNN) model with the Long Short-Term Memory (LSTM) architecture is built in Zhang-James et al. [44]to predict at-risk comorbid SUDs in individuals with ADHD improvement.
- 4. Support Vector Machines: Studies that used SVM for prediction are relatively low (five studies)[26], [65], [72], [80] as compared to other methods which are discussed above. Wang et al. compares between back-propagation neural network (BPNN), support vector machine (SVM), and logistic regression (LR) models to predict CD patients of non-adherence to azathioprine (AZA) and reports that SVM has the best performance[65]. Davoudi et al. uses various ML models including SVM to predict the risk of delirium using preoperative EHR data[24]. There are other interesting clinical studies like Wang et al.[65], also used of SVM based methodologies.

Unsupervised Learning Methods. A couple of studies used unsupervised machine learning methods. Afshar et al. [46]used LDA to identify subtypes of patients with opioid misuse whereas Cui et al. [67] used K-Means clustering and PCA to analyze and discover latent clusters inCOVID-19 patients. Kirk et. al [51] discusses an algorithm using unsupervised markov clustering (MCL) and performs a phenotypic characterization of a Danish diabetes cohort. The stratification of the diabetes cohort is based on characteristics extracted from the unstructured EHR records of the target (homogenous) population, where these characteristics include several diagnoses and lifestyle factors (SDOH). Patient clusters are obtained by exploiting unsupervised MCL along with other NLP techniques.

4. Discussion

SDOH research has become an active and interdisciplinary research domain, covering healthcare, informatics, computers science, social science. It is important to acknowledge that SDOH factors have a major impact on health outcomes. Our review indicates that various SDOH categories have been investigated with a wide range of disease categories. The most studied SDOH factors are substance abuse, employment status and socioeconomic status, whereas other important SDOH factors are under-studied, such as social environment, potentially due to the lack of data. The most studied disease areas using SDOH are mental disorders and chronic diseases. Other severe diseases (e.g., cancers) for which SDOH could be important factors for healthcare outcomes are rarely studied using the extensive information in EHRs. The associations between socioeconomic factors and health outcomes are complicated, and diverse; several pathways may be involved [98]. We observed that multiple SDOH factors are being investigated in a single disease and among the many factors, the number of SDOH factors that may potentially affect the condition of the disease is still questionable. The wide range of SDOH factors to be considered while examining the patient could indeed overwhelm the physician and may have an effect on decision-making and policymaking[99]. From our analysis, we found that most of the studies we reviewed focused on mid-and downstream SDOH factors and not upstream, like governance and policy [100]. Research on how SDOH influences establish pathways that contribute to health inequalities is much required.

In this review, we only focused on NLP techniques that were used to extract one or more SDOH aspects from clinical records. Our analysis indicates that information extraction for SDOH has been dominated by rule-based approaches, including rule-based NLP tools and methods. Half of the studies used existing clinical NLP tools, several of which (e.g., cTAKES, MetaMap) were widely used in other domains as well. Manually curated key terms were also widely used for rule-based methods. These findings are consistent with the recent review on NLP methodology for clinical IE [94]. Due to the variability of clinical concepts and limitation of hand crafted term list, unsupervised machine learning methods (word embeddings) were commonly used to expand term lists by finding their semantic similar terms in the clinical corpora. Topic modeling was another commonly used approach to cluster key terms in a coherent and latent topic. These methods often need manual check to confirm the final term list or appropriate number of topics. Very few clinical data corpora on SDOH were available, which leads to limited studies using supervised machine learning methods. However, there were a couple of studies investigating to develop SDOH specific corpus. One study utilized active learning methods, which has demonstrated to save human efforts for annotations in other studies [101]-[103]. Deep learning models have shown promising results and predominate in the general NLP domain; however, only 2 studies were found to use deep learning methods in the analyzed literature. Developing accurate deep learning models in SDOH requires a large amount of annotated training data, which is a time-consuming and labor intensive process. One possible solution is to use advanced IE techniques, such as distant supervision [104], which automatically or semi-automatically generate weak labels for training deep learning models. Predictive models were widely used to investigate the association between SDOH factors and healthcare outcomes. Such outcomes include specific diseases and administration aspects, such as readmission.

SDOH, as the data outside of traditional clinical data, is realized to provide a potential effect to understand patients' health status. People should have a better understanding of the association between SDOH and healthcare outcomes. EHR has rich information on patients' health conditions and treatment process; however, the representation of SDOH in EHR is still limited. In this review, most studies focus on one SDOH factor. Even with several papers focusing on development of NLP algorithms to extract SDOH from clinical notes, there is still a data bias regarding the representation and completeness of SDOH in EHR. Individual level SDOH information usually contributes to the accuracy of predictive models; however, they are usually hard to capture accurately or completely in EHR. There are national and regional efforts contributing to the integration of SDOH into EHRs, including establishing national standards[105] for SDOH data collection and representation [105], [106] and developing SDOH integration tools [11]. Various SDOH integration tools have emerged in order to collect more SDOH documentation in EHR. Thus, there are still a lot of efforts the community should work together to address SDOH data bias in EHR data.

AI has impacted every aspect of our daily life, from product recommendations to intelligent personal assistants, powered by the availability of large volumes of data. The increasing adoption of EHR systems in healthcare organizations has fostered the secondary use of EHR data in AI techniques to improve patient care outcomes, through clinical decision support, chronic disease management, patient education, and so forth. However, similar to human beings, AI algorithms are vulnerable to biases that may result in unfair decisions. For example, the Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) system produces a higher risk score to African-American compared to Caucasians when it is used by judges to measure the risk of committing another crime[107]. In the context of healthcare settings, bias in AI algorithms may result in more serious issues, such as affecting patients' safety, delaying

treatment, even risking lives. Therefore, addressing bias in AI algorithms is crucial for successfully deploying AI applications in healthcare and clinical practice [108]. AI bias can be summarized into two categories, i.e., data bias and algorithm bias. While algorithm bias is related to the algorithm design and model architecture that is not trivial to mitigate, data bias is relatively easier to address by carefully selecting unbiased cohorts and datasets. SDOH could serve as a metric to measure the bias in EHR data and select a fairness cohort to train AI algorithms. For example, socioeconomic status, an important SDOH variable, could be used to ensure a training dataset represents patients with different socioeconomic status.

Due to the fact that people are positioned in a social status hierarchy at birth, it influences their access to healthcare and overall disease morbidity and mortality. Health equity issues caused by complex, integrated, and overlapping social structures and economic systems are gaining recognition among scientists and public health professionals. SDOH is an important indicator for health equity since it indicates whether people have access to adequate diet, medical care, educational and career opportunities, what are their healthy environmental conditions, and whether a person is exposed to physical or psychologic trauma [109]. SDOH helps us develop comprehensive strategies to address potential risks for the population, particularly for the minority population. It is well documented that the social conditions impact premature mortality in minority communities. SDOH are responsible for many of the leading health disparities in the US. Gaining insight on the SDOH and how SDOH information could be extracted from EHRs improves the opportunities to increase wellness, prevent premature illness, gives health care teams the insight needed to increase patient action (i.e., adherence, behavior change, and compliance), provides needed information to influence health policy change for wellness, and eventually promotes health and health equity [6].

This review has several limitations. First, our search terms and databases might be insufficient to cover all studies. We only included articles written in English. Second, we only focus on studies that developed or adapted AI methods in EHR data for SDOH research. Several studies utilizing non-EHR data to study SDOH, such as clinical trial data [18], survey data [110] or claims data [13][17], were excluded from this review.

5. Conclusion

In summary, this systematic review discussed the current trends, challenges, and future directions on using SDOH from the EHR data. Our analysis indicates that despite known associations between SDOH and disease, SDOH factors are not commonly used as interventions to improve the patient's healthcare outcomes. Gaining insights into SDOH and how SDOH data could be extracted from EHRs using NLP techniques improves the opportunities to influence health policy change for patient wellness, and eventually to promote health and health equity.

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