Received: 26 May 2022 | Revised: 22 August 2022 | Accepted: 27 August 2022

DOI: 10.1111/jep.13765

ORIGINAL PAPER

Journal of Evaluation in Clinical Practice
International Journal of Public Health Policy and Health Services Research

WILEY

Social determinants of health in prognostic machine learning models for orthopaedic outcomes: A systematic review

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Abstract

Rational: Social determinants of health (SDOH) are being considered more frequently when providing orthopaedic care due to their impact on treatment outcomes. Simultaneously, prognostic machine learning (ML) models that facilitate clinical decision making have become popular tools in the field of orthopaedic surgery. When ML-driven tools are developed, it is important that the perpetuation of potential disparities is minimized. One approach is to consider SDOH during model development. To date, it remains unclear whether and how existing prognostic ML models for orthopaedic outcomes consider SDOH variables.

Objective: To investigate whether prognostic ML models for orthopaedic surgery outcomes account for SDOH, and to what extent SDOH variables are included in the final models.

Methods: A systematic search was conducted in PubMed, Embase and Cochrane for studies published up to 17 November 2020. Two reviewers independently extracted SDOH features using the PROGRESS+ framework (place of residence, race/ethnicity, Occupation, gender/sex, religion, education, social capital, socioeconomic status, 'Plus+' age, disability, and sexual orientation).

Results: The search yielded 7138 studies, of which 59 met the inclusion criteria. Across all studies, 96% (57/59) considered at least one PROGRESS+ factor during development. The most common factors were age (95%; 56/59) and gender/sex (96%; 57/59). Differential effect analyses, such as subgroup analysis, covariate adjustment, and baseline comparison, were rarely reported (10%; 6/59). The majority of models included age (92%; 54/59) and gender/sex (69%; 41/59) as final input variables. However, factors such as insurance status (7%; 4/59), marital status (7%; 4/59) and income (3%; 2/59) were seldom included.

Conclusion: The current level of reporting and consideration of SDOH during the development of prognostic ML models for orthopaedic outcomes is limited.

Healthcare providers should be critical of the models they consider using and knowledgeable regarding the quality of model development, such as adherence to recognized methodological standards. Future efforts should aim to avoid bias and disparities when developing ML-driven applications for orthopaedics.

KEYWORDS

algorithmic equity, artificial intelligence, health equity, machine learning, orthopaedic surgery, social determinants of health

1 | INTRODUCTION

In the field of orthopaedic surgery, machine learning (ML) models are becoming popular tools that aid decision making and cover a wide range of surgical outcomes, such as survival, complications and reoperation.[1–4] Specific examples include prediction models for length of stay following femoral fractures, 90-day or 1-year survival in patients with metastatic bone disease of the extremities, and discharge disposition after spine surgery.[5–7] Such models use preoperative variables, such as presence of metastatic disease, functional status, and blood values, to provide individualized risk predictions.

However, if ML model development studies do not utilize techniques to ensure algorithmic equity, they are at risk of unintended negative consequences, such as the perpetuation of health inequities. In suboptimal situations, similarities can be drawn with inequities that occur when clinical trial participants are not representative of the patient population that ultimately receives the treatment.[8] Algorithmic inequity has previously been demonstrated by Obermeyer et al.[9] who found evidence of racial bias negatively impacting Black patients in a widely used algorithm for allocating additional health resources to patients with complex health needs. Health inequities are systematic differences in the opportunities people have to achieve optimal health and arise from disparities in social determinants of health (SDOH).[10] SDOH include economic stability, living environment, educational attainment, access to care, and social support.[11]

Existing literature indicates that SDOH plays an important role in outcomes after musculoskeletal surgery.[12-15] For example, Ziedas et al. argue in a systematic review of 76 studies that for anterior cruciate ligament reconstruction, certain SDOH, including race, ethnicity, type of health insurance, and socioeconomic status, contribute to unequal access to care. Another literature review assessing complications after total hip and knee replacement for racial and ethnic minority groups found that racial and ethnic minority groups appear to have a higher risk of complications within 90 days, that is, joint infection after total knee replacement and perhaps a higher risk of mortality after total hip replacement.[16,17] A prospective study of 1220 patients undergoing total knee and hip arthroplasty demonstrated that Black race and Hispanic ethnicity were negatively correlated with patient-reported outcome measure improvement compared to White patients. Furthermore, significant associations were found based on education, sex, comorbidities, and neighbourhood poverty.[18] It has also been shown that marital status and living environment affect the duration of hospitalization and healthcare costs in patients undergoing knee arthroplasty.[19]

Based on the previously demonstrated impact that SDOH have on orthopaedic outcomes, it is necessary to consider these when developing prognostic models based on ML. However, the extent of SDOH consideration in existing prognostic ML models for orthopaedic outcomes remains unclear. Therefore, the main objectives of this review were to (1) investigate whether prognostic ML model studies account for SDOH and (2) evaluate to what extent individual SDOH variables are included in the final ML models. Findings from this review serve to inform the design of future ML models and identify areas for methodological innovation to mitigate bias and improve health equity when developing ML-based prediction models for patients undergoing orthopaedic surgery.

2 | MATERIAL AND METHODS

2.1 | Search strategy

Before initiation, this study was registered in the PROSPERO international prospective register of systematic reviews (CRD42020206522). A systematic search in collaboration with a medical professional librarian was conducted in PubMed, Embase and Cochrane for studies published up to 17 November 2020. Terms and keywords of different medical subject headings (MeSH) were combined with 'AND'. The following two domains with related words were included in the search: ML and orthopaedic specialties (Appendix 1). The PRISMA guidelines were used as reporting guidelines (Figure 1).[20]

2.2 | Eligibility criteria

Studies were included if they evaluated ML models for any prediction in an orthopaedic surgery outcome, such as survival, patient-reported outcome measures or complications.[1,2] Exclusion criteria were: (1) non-ML techniques (such as standard logistic or linear regression),

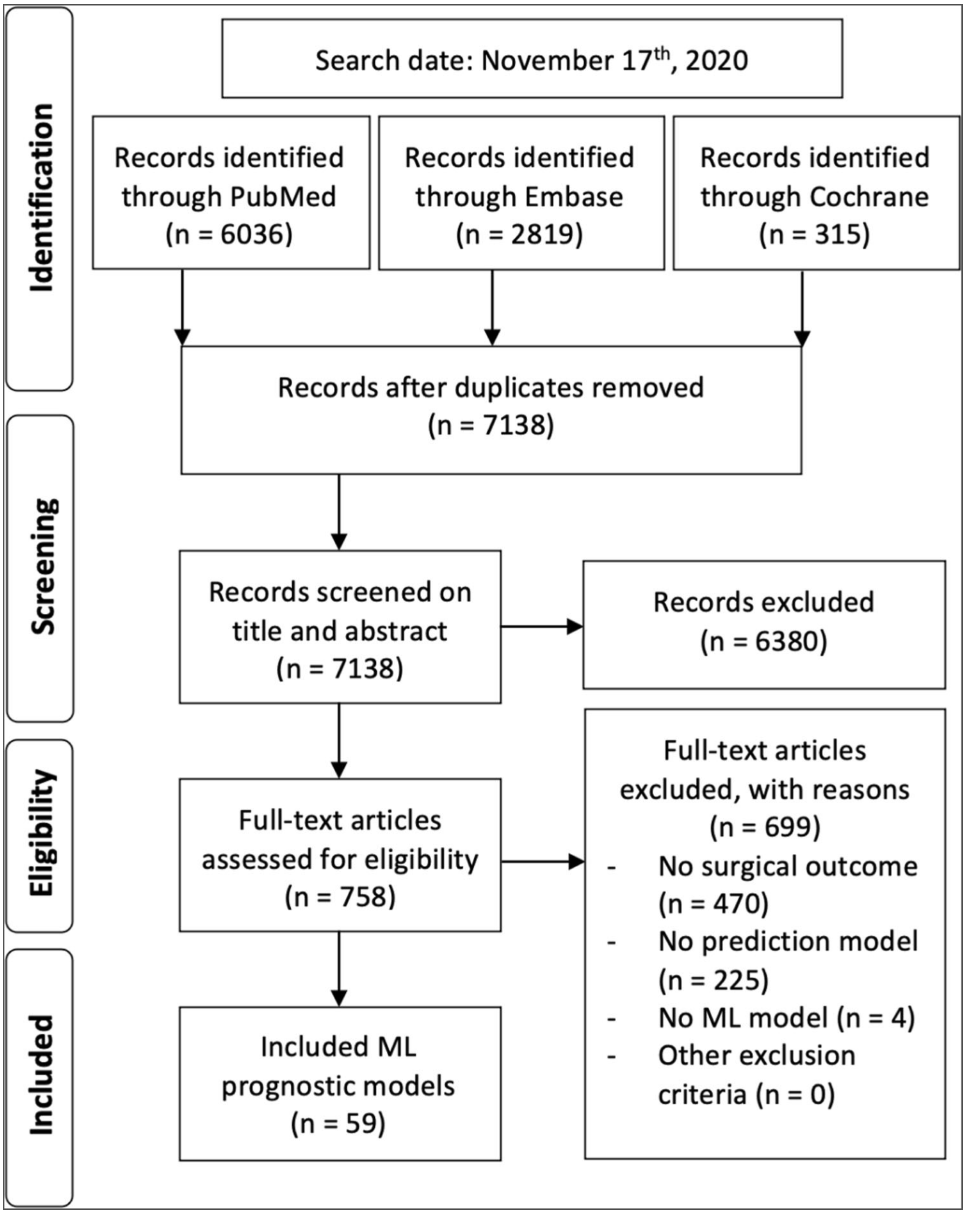

FIGURE 1 Flowchart of included studies

(2) conference abstracts, (3) non-English studies, (4) unavailability of full-text through library, and (5) nonrelevant study types such as animal studies, letters to the editors, and case-reports. Orthopaedic specialties were defined as any operation for patients with musculoskeletal disorders.

2.3 | Data extraction

Two investigators (O.Q.G., P.T.O.) independently performed identification and screening of titles and abstracts, and eligibility assessment. Any disagreements were adjudicated by the principal investigator (J.H.S.) of the study. The subsequent data extraction from the included studies was conducted independently by two reviewers (A.L., L.N.K.) and disagreements were resolved by a third investigator (O.Q.G.).

The following variables were extracted from each of the included studies: name of first author, year of publication, journal of publication, title, sample size, data sources, predicted outcome, Prediction model study Risk Of Bias Tool (PROBAST) domains, SDOH/PROGRESS+ items, differential analysis (subgroup analysis, covariate adjustment and baseline comparison), and predictors included in final model.[21]

To assess the quality of the included studies, the PROBAST tool was used. PROBAST assesses the risk of bias of a study that validates a prognostic prediction model.[22] The following domains were assessed: (1) participants, (2) predictors, (3) outcome and (4) analysis.

The SDOH were extracted using the PROGRESS+ framework (Appendix 2).[21,23] This framework is a tool first published in 2014 to guide equity analyses and to ensure explicit consideration of equity in the design of new intervention studies and in systematic reviews. In 2016 the additional items 'Plus+' were introduced. The PROGRESS+ framework consists of the following characteristics: place of residence, race/ethnicity/culture/language, occupation, gender/sex, religion, education, socioeconomic status, social capital, plus personal characteristics associated with discrimination (e.g., age, disability), features of relationships (e.g., smoking parents/excluded from school), and time-dependent relationships (e.g., leaving the hospital). Individual SDOH features were included in the final model. Individual SDOH features considered were age, gender/sex, health status, marital status, insurance status, race/ethnicity, income, built environment, and employment status.

2.4 | Software

The data extracted from each study were visualized using bar graphs (Microsoft Excel Version 19.11). Mendeley Desktop Version 1.19.4 (Mendeley Ltd) was used as a reference management software.

3 | RESULTS

The search resulted in 7138 studies which were screened by title and abstract, yielding 758 articles. After full-text assessment, 59 studies remained (Table 1 and Supporting Information: Appendix 3). The most common orthopaedic subspecialty for which models were developed was spine (48%; 27/59), followed by arthroplasty (19%; 17/59). The least common subspecialties were oncology (8%; 5/59) and sports (3%; 2/59).

3.1 | Reporting of SDOH of and PROGRESS+

Of the 59 studies, 97% (57/59) considered at least one PROGRESS+ factor during the model development stage. The most common were gender/sex (97%; 57/59), age (95%; 56/59), race or ethnicity (35%; 21/59), and socioeconomic status (17%; 10/59) (Figure 2). Differential effect analyses such as subgroup analysis, covariate adjustment, and baseline comparison were rarely reported by studies (16%; 10/59). Subgroup or interaction analyses exploring different effects across at least one PROGESS+ factor were only reported in 12% (7/59) of studies.

The median number of predictors which were included in the final ML model was 10 (interquartile range [IQR]: 7–14). When considering age, gender/sex, health status, race or ethnicity, marital status, built environment, educational attainment, insurance status, and income as SDOH features, the median number of SDOH features included in final models was 2 (IQR: 2–3). During feature selection, 49% (29/59) of the studies considered additional SDOH and 12% (7/59) did not consider any SDOH variables besides age and gender/sex. When excluding age and gender/sex as SDOH variables, the median number of SDOH features included in the final risk prediction models was 1 (IQR: 0–1) (Table 2 and Figure 3). When looking at the mean number of SDOH features included per subspecialty, we found that sports most often incorporated SDOH features ($n = 3.5$). However, there were only two sports studies among the included studies. The lowest mean number of SDOH features was in oncology ($n = 1.2$). However, there were only five oncology studies. Most of the studies were in the subspecialties spine ($n = 27$) and arthroplasty ($n = 17$), both of which had a mean incorporation of SDOH features of 2.7 (Appendix 4).

TABLE 1 Characteristics of included studies

	Median (IQR[a])
Sample size	4.782 (616–23,264)
Data sources	*% (n)*
Prospective database	3 (5)
National/Registry database[a]	47 (28)
Year of publication	
<2017	22 (13)
>2018	78 (46)
Subspecialty	
Spine	27 (48)
Arthroplasty	17 (29)
Trauma	8 (14)
Oncology	5 (8)
Sports	2 (3)
Predicted outcome	
Complications	24 (14)
Patient-reported outcome measures	20 (12)
Mortality	19 (11)
Health management	19 (11)
Other	19 (11)

Abbreviation: IQR, interquartile range.
[a]This includes databases such as Surveillance, Epidemiology, and End Results (SEER) or the American College of Surgeons National Surgical Quality Improvement Program (ACS NSQIP).

3.1.1 | Risk of bias assessment

Across all included studies the overall risk of bias was high or unclear in 56% (33/59) and low in 44% (26/59) (Figure 4). Bias in the analysis domain, for reasons such as inadequate handling of missing data or small data sets, was the most common reason studies were rated with a high overall risk of bias (41%; 24/59).

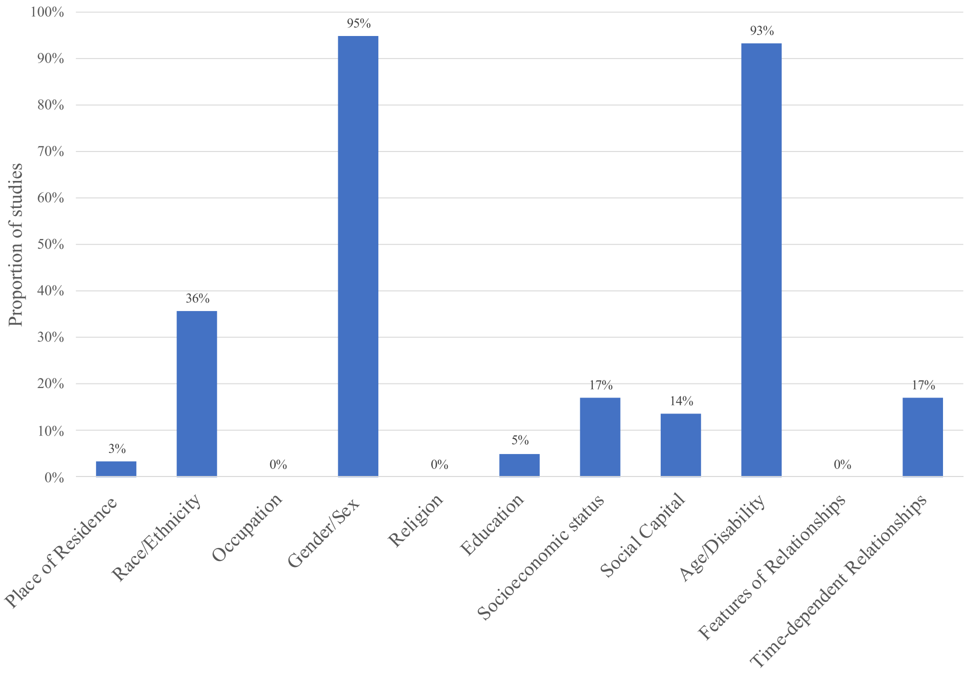

FIGURE 2 PROGRESS+ factors considered as features during the development of machine learning models

TABLE 2 Variables included in final models

	Median (IQR)
Predictors included in final model[a]	10 (7–14)
SDOH variables included[b]	2 (2–3)
SDOH§ variables excluding Age & Gender/Sex	1 (0–1)
Individual features	***% (n)***
Age	92 (54)
Sex	69 (41)
Health status	47 (28)
Race/ethnicity	25 (15)
Built environment	7 (4)
Educational attainment	7 (4)
Marital status	5 (3)
Employment status	3 (2)
Insurance status	2 (1)
Income	0 (0)

Abbreviations: IQR, interquartile range; SDOH, social determinant(s) of health.

[a]The number of predictors that were included in the final, best-performing machine learning algorithm. For nine studies these data were not available.

[b]SDOH variables: age, sex, health status, race/ethnicity, educational attainment, marital status, employment status, income, insurance status, living environment.

4 | DISCUSSION

In this systematic review, we found that the majority of included ML model studies reported at least one SDOH, namely gender/sex and age. It is expected that these basic variables are reported in most studies, as they have consistently been shown to have prognostic value. This study also found that the consideration of SDOH variables during feature selection and the inclusion of SDOH features in the final model was limited. If excluding the basic demographic variables of age and gender/sex, SDOH were rarely considered. These findings suggest that notable biases may exist in ML models currently developed in orthopaedic literature. Therefore, to avoid exacerbating disparities, ML models must be translated into clinical care with caution.

In orthopaedic surgery, various components of SDOH, including race/ethnicity, educational attainment, socioeconomic status, and social context, are reported to have an impact on health outcomes, such as length of stay, patient-reported outcome measures, and revision surgery.[19,24-28] Therefore, lack of reporting of basic demographic characteristics or failure to justify why certain factors are excluded during model development may limit the quality and impact performance of the model. An example of this can also be found in the studies included in the current investigation. Of the 59 included studies, 21 considered race or ethnicity during their model development, where 15 ultimately included race or ethnicity in the final model. This indicates that most studies did not consider race or ethnicity as features and only 6 studies demonstrated that these

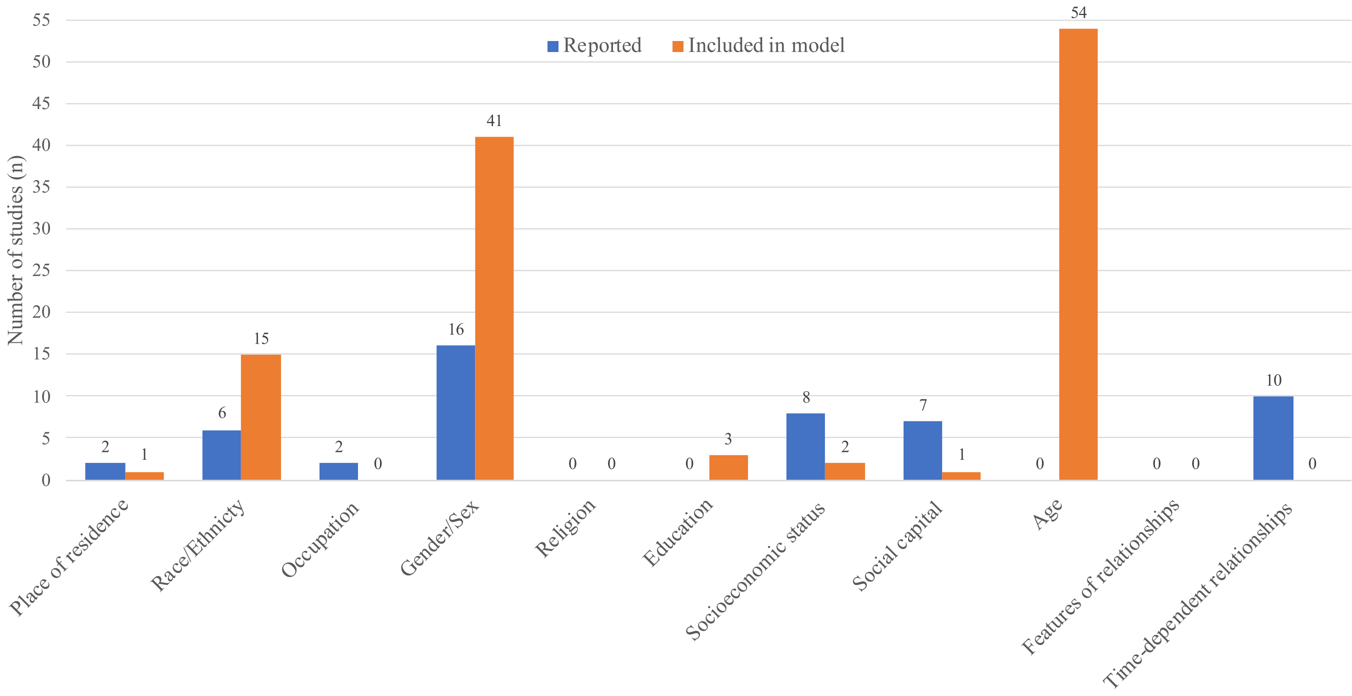

FIGURE 3 Frequency of induvial social determinants of health (SDOH) reported (blue) and the rate of individual SDOH included as features in final machine-learning models (orange)

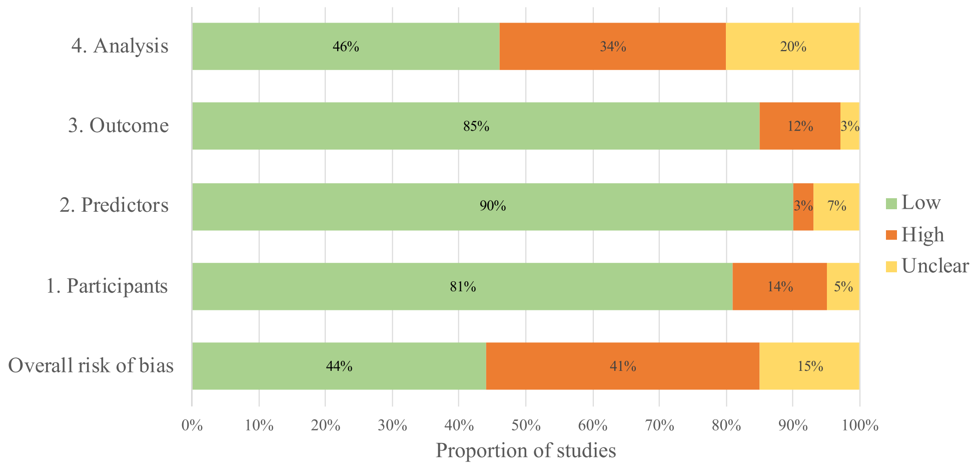

FIGURE 4 Prediction model study Risk Of Bias Tool (PROBAST) assessment for all included studies

features were not suitable for their model. Although SDOH indicators may not always be appropriate for an ML model, the addition of SDOH indicators in risk adjustment models has previously been demonstrated to reduce disparities in several vulnerable populations.[29] Additionally, unfamiliarity with potentially biased data may cause unintended propagation of existing systemic inequalities. Although the concept of inequity in health care is not novel or unique to the prognostic modelling for orthopaedic surgery, it should still be deemed important to aim at mitigating biases, regardless of which approach is used. As we increase to rely on ML-driven algorithmic decision aids in clinical practice, it will be vital that these models are held to a high equitable standard.

4.1 | Recommendations

The findings of this review provide researchers who are developing ML models for orthopaedic purposes with insights on the inclusion of SDOH and how it can impact the quality of their models. Guidelines for transparent reporting have previously been developed; however, adherence has also been found to be poor.[30,31] Building on this prior work, we recommend that researchers additionally take into account and report SDOH features that have been shown to impact surgical outcomes in orthopaedics and should be incorporated into reporting guidelines.[17,18] We recognize that this may be challenging, but frameworks such as the PROGRESS+ can be used as a tool to guide equity analyses for researchers to ensure explicit consideration of equity in the design of new ML models.[23] However, the limitations of the PROGRESS+ must also be taken into account, such as the rudimentary definitions of SDOH. For example, the guideline uses either race/ethnicity/culture or language as a measurement of race/ethnicity. How these data are recorded is also important, as there is a difference in self-reported or object measures. Furthermore, studies often use gender and sex interchangeably, even though these two terms have different definitions. The WHO defines 'sex' as the 'biological and physiological characteristics that define men and women'. The WHO further defines 'gender' as the 'socially constructed roles, behaviours, activities and attributes that a given society considers appropriate for men and women'.[32,33] Standardization of definitions and reporting guidelines may improve the quality of data used to train models. This will help identify disparities or bias which in turn can be addressed. However, to our knowledge, there is no recognized framework for reporting SDOH in medical literature other than PROGRESS+.[34] Therefore, the context in which the model is intended to be used must be taken into account, as this plays a role in determining which inequalities may drive inequities.[35] In some instances certain PROGRESS+ factors may be especially important, such as social capital with respect to discharge disposition. An additional consideration when using a framework such as PROGRESS+ is that some factors may change over time, for example, marital status and income, whereas others, such as race/ethnicity, do not. The impact these changes may have on the model should be evaluated and considered during the development and updating of models. Finally, SDOH may not always be appropriate features for the intended use of the ML model. They may not be independent predictors or simply are not readily available. However, transparent reporting of data deficits and limitations should be required. Additionally, investigators must provide justification when omitting features that are generally known to be of prognostic value (i.e., age and sex). Without this, it will be challenging for the reader to fairly evaluate the quality and usability of ML models.

4.2 | LIMITATIONS

This study is not without limitations. First, despite the use of multiple online medical databases and comprehensive search strategies, studies may have been missed. However, we do not believe that the possibility of this impacts the findings of this study as we included over 50 studies. Second, the PROGRESS+ framework was used as a reporting benchmark. However, acceptable scores and the relative importance of domain is yet to be defined and subject to the context of each model and its intended use. Additionally, we reported if studies included a subgroup analysis but did not note if this would be appropriate for the study in terms of power or if prompted by a hypothesis. Therefore, the finding that hardly any studies did such an analysis should be seen in light of this limitation. Despite these limitations, this review offers profound insights into the reporting and use of SDOH in ML-driven prognostic tools for orthopaedic surgery and provides a reference for future assessments of SDOH reporting.

5 | CONCLUSION

The current reporting and consideration of various SDOH for the development of prognostic ML models for orthopaedics is limited. ML-based prediction models can support clinical decision making, but healthcare providers should be aware of the models they consider using based on the data used to develop them. Knowledge regarding the quality of model development, such as adherence to recognized methodological standards, should always be considered. ML is useful in orthopaedic surgery; however, if these models are integrated into clinical care, they should consider reporting SDOH factors. Future efforts should aim to avoid bias and disparities when developing machine learning-driven applications for orthopaedics.

AUTHOR CONTRIBUTIONS

Amanda Lans: Conceptualization, methodology, formal analysis, investigation, writing–original draft, writing–review & editing. **Laura N. Kanbier**: Conceptualization methodology, formal analysis, investigation, writing–original draft. **David N. Bernstein** and **Daniel G. Tobert**: Writing–original draft, writing–review & editing. **Olivier Q. Groot**: Conceptualization, methodology, investigation, writing–review & editing. **Paul T. Ogink**: Methodology, investigation. **Jorrit-Jan Verlaan** and **Joseph H. Schwab**: Conceptualization, supervision, writing–review & editing.

CONFLICT OF INTEREST

The authors declare no conflict of interest.

DATA AVAILABILITY STATEMENT

Data sharing not applicable to this article as no datasets were generated or analysed during the current study.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

How to cite this article: Lans A, Kanbier LN, Bernstein DN, et al. Social determinants of health in prognostic machine learning models for orthopaedic outcomes: a systematic review. *J Eval Clin Pract*. 2023;29:292-299. doi:10.1111/jep.13765