Review

Clinician involvement in research on machine learning–based predictive clinical decision support for the hospital setting: A scoping review

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ABSTRACT

Objective: The study sought to describe the prevalence and nature of clinical expert involvement in the development, evaluation, and implementation of clinical decision support systems (CDSSs) that utilize machine learning to analyze electronic health record data to assist nurses and physicians in prognostic and treatment decision making (ie, predictive CDSSs) in the hospital.

Materials and Methods: A systematic search of PubMed, CINAHL, and IEEE Xplore and hand-searching of relevant conference proceedings were conducted to identify eligible articles. Empirical studies of predictive CDSSs using electronic health record data for nurses or physicians in the hospital setting published in the last 5 years in peer-reviewed journals or conference proceedings were eligible for synthesis. Data from eligible studies regarding clinician involvement, stage in system design, predictive CDSS intention, and target clinician were charted and summarized.

Results: Eighty studies met eligibility criteria. Clinical expert involvement was most prevalent at the beginning and late stages of system design. Most articles (95%) described developing and evaluating machine learning models, 28% of which described involving clinical experts, with nearly half functioning to verify the clinical correctness or relevance of the model (47%).

Discussion: Involvement of clinical experts in predictive CDSS design should be explicitly reported in publications and evaluated for the potential to overcome predictive CDSS adoption challenges.

Conclusions: If present, clinical expert involvement is most prevalent when predictive CDSS specifications are made or when system implementations are evaluated. However, clinical experts are less prevalent in developmental stages to verify clinical correctness, select model features, preprocess data, or serve as a gold standard.

Key words: clinical decision support, machine learning, electronic health records, nurses; physicians; hospitals

INTRODUCTION

Machine learning, a type of artificial intelligence that involves computers initiating and executing learning from data without human intervention,[1] is being increasingly applied in the health care domain

for prognostication and treatment.[2,3] Examples span specialties and settings from predicting risk for poor glycemic control among patients with diabetes,[4] to forecasting likely interventions in the intensive care unit (ICU).[5] The pace of machine learning research in

health care, for any purpose, is especially increased by the ubiquity of electronic health records (EHRs), which store large volumes of patient data.

Many machine learning models that make prognosis or treatment predictions are intended to be used in clinical decision support systems (CDSSs) to assist clinicians in making informed decisions about patient care. Historically, CDSSs have used known relationships between variables in patient data to provide clinicians with evidence-based recommendations, alerts, or patient summaries to support their decision making.[6,7] Alternatively, machine-learning-based CDSSs, which use relationships between patient variables and target outputs learned by the machine learning model, face challenges to clinician adoption.[8–10] Shortliffe and Sepúlveda[10] recently outlined 6 challenges to CDSS in "the era of artificial intelligence": (1) complicated models lack transparency, which prohibits clinicians' ability to understand and accept predictions or recommendations; (2) clinician time is scarce; (3) systems must be usable and easily learnable; (4) recommendations must be relevant to the clinicians in the targeted domain; (5) delivery must respect clinician expertise; and (6) recommendations must be based on rigorous science. Many of these challenges apply to CDSSs that do not use machine learning (ie, expert systems). For example, all CDSSs must be usable. However, machine learning offers unique technical capabilities that exacerbate these challenges. For example, investigators can engineer new features not present in the original dataset, creating a model likely more difficult to quickly understand as an end user than a system using Boolean logic on original data. Additionally, while all listed challenges apply to machine-learning-based CDSS for any type of clinical decision (eg, diagnosis, prognosis, treatment) in any setting (eg, outpatient, inpatient), they are especially difficult when systems are designed (1) to assist with prognosis or treatment decision making (hereafter referred to as, predictive CDSSs) and (2) for the hospital setting. This is because, unlike many diagnostic decisions, prognosis and treatment decisions often cannot be linked to a gold standard, such as a biopsy. Even expert clinicians may disagree.[10] Additionally, in the hospital setting, clinicians are under increased time pressure and making decisions that impact the patient in the immediate or near terms.[11,12]

Addressing each of the challenges outlined previously requires interdisciplinary collaboration between experts in informatics, data science, human factors, and the clinical domain that the system aims to target. For example, to mitigate the issues of model transparency and understandability, researchers have suggested using domain knowledge to assess model complexity[3] or to identify features likely to prove reasonable to an end user.[13] However, as machine learning is increasingly researched (eg, PubMed articles tagged with the "machine learning" MeSH [Medical Subject Heading] Major Topic increased by nearly 10-fold from 2014 to 2019)[14] and applied to clinical decision making, it is unclear the frequency with and capacity in which clinical experts are involved in predictive CDSS development, evaluation, and implementation.

The process of building and testing a predictive CDSS for use in a hospital setting can be situated within Stead et al's[15] framework describing medical informatics system design. The framework has 5 sequential stages: (1) specification, (2) component development, (3) combination of components into system, (4) integration of system into environment, and (5) routine use. The specification stage involves eliciting system needs and technical functionalities from end users. The component development stage involves development of an "isolatable subset of a system"[15] with clear inputs and outputs. In predictive CDSS design, these components might include the machine learning model, the CDSS interface, the database, etc. Combination of components into a system involves integrating previously developed components. Integration of system into environment involves incorporating the system into the technical and cultural ecosystem in the intended setting. Finally, routine use is achieved when the system is a normal function of work in the environment.[15] Each successive stage depends on rigorous evaluation of the previous.[15,16]

Though the routine use stage will inherently involve clinicians, it is possible for developers and investigators of predictive CDSSs to move through the other stages with or without engaging clinical experts, potentially missing an opportunity to mitigate 1 or more known challenges to adoption. The objective of this review is to describe the literature on predictive CDSS research for in-hospital decision making as it pertains to clinician involvement in Stead et al's 5 stages of system design. A scoping review is best suited to this objective because the intent is both (1) to examine the range and nature of research on this topic and (2) to inform future research and development.[17–19] Our ultimate goal is to inform the broader discourse on rigorous methods for overcoming challenges to predictive CDSS adoption.

MATERIALS AND METHODS

Information sources and search terms

This scoping review was conducted following the PRISMA-ScR (Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews) guidelines (Supplementary Table 1).[20] Three scholarly databases were searched in October 2019: PubMed, CINAHL, and IEEE Xplore; proceedings from the Machine Learning for Healthcare conference and CHI: Conference on Human Factors in Computing Systems were hand searched in May 2020. Our search strategy combined terms representing 3 elements of the topic of interest: machine learning, clinical decision support, and clinicians. Keywords were identified to represent each element as comprehensively as possible, searched using truncation and standardized subject headings when appropriate, and combined using Boolean operators (Supplementary Table 2).

Eligibility criteria

Inclusion and exclusion criteria are presented in Table 1. Publications describing predictive CDSS targeting nurses, physicians, or advanced practice providers for prognostic or treatment decision making in the hospital using EHR data were included.

We focused on systems using EHR data because EHRs are the primary health information system clinicians use in patient care and thus, are rich with potential signals for predicting patient outcomes. EHR data also present unique complexity (eg, varying temporal granularity) and opportunity for clinical expertise. Publication year was limited to the last 5 years given the rapid evolution of machine learning science.[21,22] For example, deep learning research in health care has exponentially increased,[22,23] reflecting a broader evolution in technical methods and thus evolving opportunities for clinical expert involvement.

Imaging and pathology interpretation systems were excluded because they are not strictly hospital-based and represent computer-assisted diagnosis. We determined if described models were for a CDSS according to the article's stated goal and its alignment with patient care workflows. For example, modeling research database searches were excluded.

Table 1. Study eligibility criteria

Inclusion criteria	Exclusion criteria
• Empirical studies published in peer-reviewed journals or conference proceedings • Published between 2015 and 2019 • Describe development, evaluation, or implementation of predictive CDSS for decision making in the acute care, intensive care, or ED settings • Describe a predictive CDSS for use by nurses, physicians, or advanced practice providers (ie, nurse practitioners or physician assistants) • Used or intend to use EHR data for model development	• Articles not available in English • Systematic reviews • Conference abstracts • Used non-EHR health information system data (eg, ECG tracings) • Used clinical trial data not reflective of real-world patient care and/or documentation • CDSS for patients • CDSS in the outpatient setting • Did not describe the intended setting of predictive CDSS and described a decision that could occur outside the hospital (eg, long-term chemotherapy regimen) • Computer-assisted diagnosis (ie, CDSS for diagnosis) • Imaging or pathology interpretation

Note: CDSS: clinical decision support system; ECG: electrocardiogram; ED: emergency department; EHR: electronic health record.

To operationalize our criteria, we defined machine learning a priori by referencing Beam and Kohane,[24] who defined machine learning as a spectrum from minimal to maximal machine involvement. Using their spectrum, we included machine learning models with more machine involvement than linear and logistic regression.[1,24] Though standard regression models are frequently used for machine learning, because they are at the bottom of the machine involvement spectrum, they are less computationally complex and standardly require human involvement. Thus, clinical expert involvement in regression model design is expected and challenges to adoption (eg, model transparency) are less likely to apply. More computationally complex models offer novel opportunities for modeling complex relationships[25] and for clinician involvement.

Data screening and charting
Two authors (J.M.S. and K.D.C.) screened titles and abstracts of identified articles for eligibility criteria. A calibration exercise was conducted between the 2 screening authors with approximately 50 titles or abstracts. A third author (A.J.M.) resolved any screening disagreements and any disagreements between the 3 authors were discussed until a consensus was reached. Two authors (J.M.S. and K.D.C.) reviewed the full texts of remaining articles. Reference lists of included articles were reviewed to identify additional articles meeting criteria. Covidence software (Covidence, Melbourne, Australia) was used to assist with screening.[26]

Data charting was completed by one author (J.M.S.) using Microsoft Excel and Word (Microsoft Corporation, Redmond, WA)[27] and verified by a second author (K.D.C.). Data items extracted include study characteristics such as country of origin, clinical specialty, study design, method of machine learning model(s) described, and size of cohort used to train and test the model or number of clinicians who evaluated a system. Charted items related to the review objective include the study objective, model outcomes, target decision maker (eg, nurses or physicians), stage(s) in system design,[15] and clinician involvement. Author affiliation or licensure was charted subsequently to provide perspective on the possibility that authors may have served as clinical experts themselves.

Charting of particular data items involved our interpretation. If the authors did not specify if the system was intended for nurses or providers, the term "clinician" is used. Similarly, when the profession of clinicians involved was not explicitly stated, we used the term "clinical experts." General indicative language such as "based on expert medical knowledge and opinion"[28] was charted as clinical expert involvement. Study objectives are not direct quotes, but one author's (J.M.S.) summary. The stage in system design was not explicitly stated in any of the articles. Stead et al's framework[15] and its subsequent elaboration by Kaufman et al[16] were used to identify the aligned stage. Additionally, the charted study location is the country where the majority of investigators are affiliated and does not necessarily reflect the location of the data source. We have also described the machine learning model method according to a larger class in many cases. For example, "neural networks" is used to describe studies that involved any type of neural network (eg, backpropagation or convolutional). This serves 2 purposes: (1) synthesis of model methods and (2) clarity for an audience not necessarily expert in machine learning.

RESULTS

The initial database search yielded 1621 articles (Figure 1). Seventy-eight additional articles were identified from hand-searching conference proceedings and reference lists. After duplicates were removed, 1142 article titles or abstracts were screened. A total of 926 articles were excluded in title or abstract screening, leaving 216 full-text articles assessed for eligibility. A total of 136 articles were excluded after full-text screening, leaving 80 articles eligible for synthesis.

Summary of study characteristics
Table 2 summarizes the characteristics of the 80 included studies (further detailed in Supplementary Table 3). Studies were primarily of retrospective cohort design (n = 66), were conducted in the United States (n = 55), were published in 2019 (n = 23), were designed for intensive care (n = 37), and used neural networks (n = 34).

Predictive CDSSs and clinician involvement
Clinician involvement according to system design stage is summarized in Table 3 and further detailed along with decision-support objectives, machine learning model outcomes, target clinicians, and author affiliation in Supplementary Table 4. Most study authors described decision support for clinicians nonspecifically (n = 50). Fewer targeted physicians only (n = 18), nurses only (n = 5), or either nurses or physicians or providers (n = 4), with 1 including respiratory therapists.[101] Three studies specifically identified hospital interprofessional rapid response teams as target end users.[29–31]
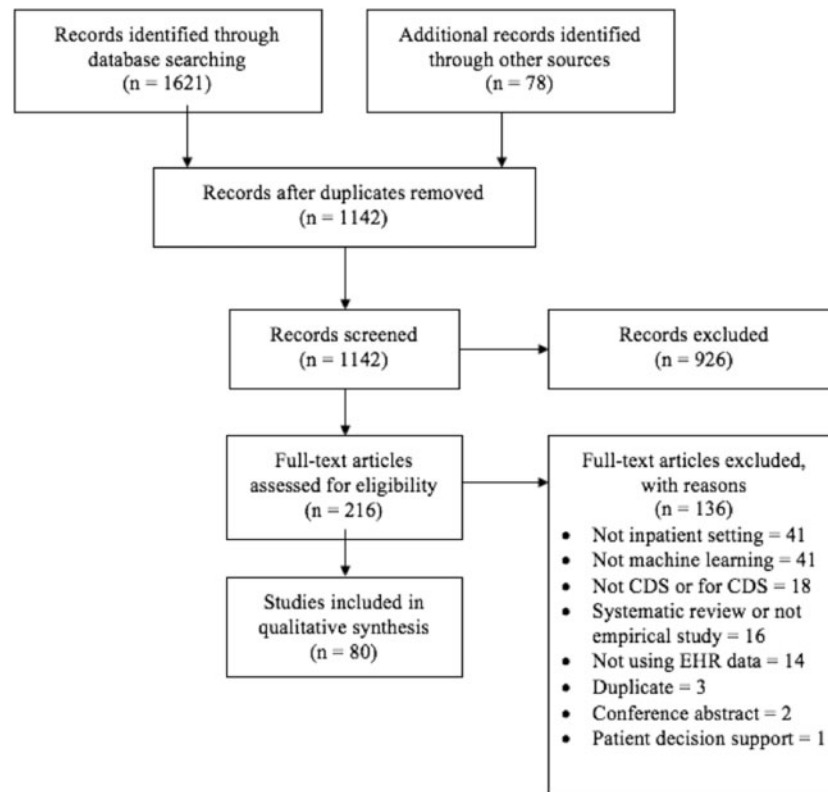
Figure 1. PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram of study eligibility screening. CDS: clinical decision support; EHR: electronic health record.

Studies investigated predicting a variety of target outcomes (Supplementary Table 4). The most common were mortality (both after discharge and in-hospital; n = 31), sepsis and septic shock (n = 16), transfer to the ICU (n = 6), ICU or hospital readmission (n = 6), and length of stay (n = 5).

Specification

Three studies investigated the specification stage of predictive CDSS, each seeking to illuminate the needs of clinicians using predictive CDSS at varying levels of specificity—all of which involved clinical experts. ICU clinicians were interviewed to specify their predictive CDSS needs for patient monitoring.[101] Clinicians in the emergency department and ICU were interviewed to understand when and how explanations are needed to understand predictive CDSSs.[12] Finally, clinicians in cardiology co-designed a predictive CDSS for ventricular assist device decision making and advised on fit with clinical workflow.[102]

Component development

Of the 76 studies describing component development, 21 (28%) involved clinical experts in this stage. All component development studies described developing the machine learning model. Clinical expert involvement in component development can be organized into 5 categories: clinical relevance or correctness,[28,31–38,93] feature selection,[35,38–41,93,94,98] data preprocessing,[5,42–44] gold standard,[35,37,45,99] and no clinician involvement described.[29,30,46–92,95,96,100,103–105]

Clinical relevance or correctness

Of the 21 studies involving clinical experts in the component development stage, nearly half (n = 10) involved clinical experts advising on the clinical relevance or correctness of the model(s). Clinicians set performance requirements such as sensitivity, specificity, and false positive rates,[33,93] and established alert trigger thresholds.[93] Alternatively, clinicians advised on model outcomes – defining outcomes[31,34] or identifying their presence in the data.[34–36] Clinicians also helped to derive meaning from features.[28,32,36,37] For example, Jalali et al[28] consulted clinical experts to group features by body organ to improve their mortality model and its intuitiveness in the ICU. More broadly, clinical experts advised on implications for clinical practice[34,36] and research design.[38]

Feature selection

Eight studies included clinical experts in determining which features should be used as inputs in the machine learning model—something that can be done according to domain knowledge or purely using computational methods. Clinical experts functioned to both narrow down the set of all possible features available from their datasets[38–40,94] and to identify candidate features from which to start working.[35,41,93,98] Half of these studies additionally used computational feature selection methods.[39,40,93,98]

Data preprocessing

Four studies involved clinical experts in data preprocessing. Clinical experts advised on the periodicity of interventions in practice, from which investigators established intervention gap thresholds for interpolation in their forecasting model.[5] In 2 studies, clinicians identified

Table 2. Summary of study characteristics

Characteristic	Variable	Results
Study Design	Retrospective cohort	66 (82.5)[5,28–92]
	Prospective cohort	5 (6.3)[93–97]
	Case-control	3 (3.8)[98–100]
	Qualitative	3 (3.8)[12,101,102]
	Retrospective + prospective cohort	3 (3.8)[103–105]
Location[a]	United States	55 (68.8)[5,28,29,31,32,34,36,40–44,47–50,52,54–60,62,63,65–70,73–80,82,83,85,90–93,95,97–100,102,104,105]
	United Kingdom	7 (8.8)[39,53,55,61,63,67,77]
	Taiwan	5 (6.3)[38,39,45,67,88]
	Canada	4 (5)[12,33,81,87]
	China	4 (5)[37,39,71,103]
	Australia	3 (3.8)[86,94,96]
	Germany	2 (2.5)[51,101]
	India	2 (2.5)[64,89]
	Switzerland	2 (2.5)[35,72]
	South Korea	1 (1.3)[30]
	Saudi Arabia	1 (1.3)[46]
	Spain	1 (1.3)[84]
	France	1 (1.3)[76]
	Portugal	1 (1.3)[75]
Year	2019	23 (28.8)[12,42,43,60,64,65,67,68,70,72,79,82,83,92,95–99,101–103,105]
	2018	18 (22.5)[30,36,39,41,46,61,63,66,69,71,74,78,81,88,89,91,94,104]
	2017	15 (18.8)[5,29,31,44,51–53,57,58,75,77,80,85,87,100]
	2016	12 (15)[28,32,37,40,47,49,50,62,73,84,86,93]
	2015	12 (15)[33–35,38,45,48,54–56,59,76,90]
Machine learning methods[a]	Neural networks	34 (42.5)[28–33,35,39,41,43,45,47–51,54,60,66,68,70,72,76,79–84,89,94,96,99,100]
	Random forests	32 (40)[30,35–38,40,42–44,49–51,54,57,63–66,71,76,79,83,88,90,91,94,95,97,98,103–105]
	Regression[b]	27 (33.8)[30,32,35,39–41,43,47,48,50,54,56,61,62,65,70,76,79,83,84,87,88,90–92,94,95]
	Support vector machines	24 (30)[32,34,35,37–39,44,46–48,50,51,55–57,59,61,62,66,75,79,94,98,103]
	Boosting	17 (21.3)[32,47,49,50,52,53,65–67,69,76,78,90,91,94,98,103]
	Decision trees	15 (18.8)[32,35,38–40,47,48,50,52,53,56,62,76,78,88]
	Penalized regression[c]	13 (16.3)[5,35,37,44,55,57,65,66,91,95,98,100,103]
	Bayesian	13 (16.3)[5,35,37,39,44,57,62,66,76,79,86,93,98]
	Topic modeling	9 (11.3)[55,57,59,66,79,80,85,91,99]
	Ensemble	7 (8.8)[52,53,62,76,78,81,95]
	Nearest neighbors	6 (7.5)[35,50,54,72,98,103]
	Gaussian process	5 (6.3)[5,29,31,55,98]
	Clustering	5 (6.3)[51,61,87,89,92]
	Reinforcement learning	4 (5)[34,63,73,77]
	Generalized additive models	3 (3.8)[76,90,95]
	Bagging	3 (3.8)[35,50,76]
	Discriminant analysis	2 (2.5)[35,61]
	Word vectorization	2 (2.5)[64,89]
	Other methods[d]	10 (12.5)[32,35,37,44,54,58,72,74–76]
Sample size	Qualitative	10-19 clinicians
	Model development	127 patients to 296,724 hospital admissions
Clinical specialty[a]	Intensive care (adult)	37 (46.3)[5,12,28,30,34,43,44,51–53,55,56,58–61,63,64,66–69,71–77,79,80,83,86,87,89,91,101]
	In-hospital, acute care/not further specified	14 (17.5)[30,31,34,46,50,54,69,82,85,90,97,103–105]
	Emergency medicine	14 (17.5)[12,35,36,40,42,57,69,84,86,88,90,93,95,99]
	Cardiology	7 (8.8)[37,71,81,86,88,92,102]
	Pediatric (acute and intensive care)	6 (7.5)[32,58,70,78,81,100]
	Nephrology	5 (6.3)[62,66,75,79,83]
	Neonatal intensive care	4 (5)[33,94,96,98]
	Stroke	4 (5)[47–49,86]
	Surgery	3 (3.8)[38,41,86]
	Diabetes	2 (2.5)[39,65]
	Pulmonology/respiratory	2 (2.5)[42,90]
	Nursing	1 (1.3)[45]
	Trauma	1 (1.3)[95]

(continued)

Table 2. continued

Characteristic	Variable	Results
	In-hospital, specifically: emergency medicine, intensive care, cardiothoracic surgery/transplant, neurology/vascular/stroke, gastrointestinal, oncology/hematology/immunology/pharmacology	1 (1.3)[86]

Values are n (%) or range.

[a]Studies may fall into more than 1 category.

[b]Does not meet our definition of machine learning but included for purposes of reporting all methods authors compared.

[c]Including LASSO, Ridge, and Elastic Net.

[d]Generalized linear models, conditional inference recursive partition, conditional random fields, Weibull-Cox proportional hazards, lazy learner, piecewise-constant conditional intensity model, analysis of covariance (see footnote b), analysis of variance (see footnote b), fuzzy modeling (see footnote b), switching-state autoregressive model, mimic learning, nearest shrunken centroids, J48 algorithm, PART rule.

Table 3. Summary of findings of clinician involvement by stage of system design

Clinician Involvement Category	Clinician Involvement Details	Results
Specification		3 (4)
Identified system needs and design	Clinicians interviewed regarding: • ICU monitoring needs[101] • prediction explanations[12] • design and fit with workflow[102]	3 (100)
Component development		76 (95)
Clinical relevance/correctness	• Corroborated significance of partial dependence plots[32] • Judged suitability of research design[38] • Defined outcomes[31,34] • Deemed features coherent and informative[37] • Grouped features by body organ[28] • Deemed outcomes present[35] • Evaluated face validity of predictors and outcomes[36] • Categorized predictors (chief complaints)[36] • Advised on implications and relevance of system in practice[34,36] • Determined sensitivity/specificity[33] and false positivity rate requirements[93] • Defined reinforcement learning reward/cost values[34] • Set alert trigger threshold[93]	10 (13)
Feature selection	• Narrowed feature set[38–40,94] • Identified features[35,41,93,98]	8 (11)
Data preprocessing	• Advised on periodicity of interventions in practice to inform interpolation thresholds[5] • Identified invalid values in data distribution[42] • Defined normal ranges for imputation and outlier removal[43] • Advised on feature construction[44]	4 (5)
Gold standard	• Annotated progress notes for description of outcome[37,99] • Documented predictor (patient severity of illness)[35] • Compared documented nursing diagnoses to standard ontology[45]	4 (5)
Combination of components into system		5 (6)
Integration of system into environment		5 (6)
Evaluation	• Small group of experts developed survey[45,97] • Larger sample of clinicians completed survey[45,97]	2 (40)
Routine use		0 (0)

Values are n (%). Some studies described more than 1 stage of design and/or method of clinician involvement. Stages based on framework outlined by Stead et al.[15]

ICU: intensive care unit.

invalid or outlier values in feature distributions.[42,43] Finally, clinical experts advised on correctly constructing features from ICU data.[44]

Gold standard

In 4 studies, clinicians established the gold standard against which model performance was judged; models either learned from clinician judgement data or were assessed based on clinician-determined ground truth. In one example, physicians documented impressions of patient severity of illness.[35] Clinicians also annotated progress notes for the presence of outcomes.[37,99] In Liao et al[45] experienced nurses compared documented nursing diagnoses to an established ontology used in model development.

No clinician involvement described

Fifty-five (72%) of the studies on component development did not mention any involvement from clinical experts.[25–28,30–34,36,50–]

[88,100,103–105,93][96] However, 4 of these studies discuss this as a future improvement.[56,65,74,82] For example, J.Y. Kwon et al.[65] positioned their paper as an argument for using nursing knowledge to improve predictive CDSSs, describing how nurse experts may have improved the performance and clinical relevance of their model.[65]

Additionally, in multiple articles, authors did not explicitly describe clinician involvement but indirectly imply using clinical expertise. For example, Kaji et al[60] mentioned identifying model features based on "known clinical relevance to [their] target end points." Each author was affiliated with a medical school.

Combination of components into system

All 5 studies that reported on combination of components into system also reported on component development. These studies either described or presented a predictive CDSS prototype or interface; none of them described involving clinical experts in this stage.[29,33,34,84,93]

Integration into environment

Five studies described integrating the system into its environment,[45,93,97,104,105] with 4 also describing component development.[45,93,104,105] Two studies involved clinical experts in evaluating the predictive CDSS after integration.[45,97] In both studies, clinicians responded to surveys evaluating their impressions of the predictive CDSS and clinicians helped develop the surveys.[45,97] For example, in Ginestra et al,[97] attending physicians, residents, and nurses helped develop an evaluation survey that was completed by 252 clinicians.

Author affiliation or licensure

It is possible that clinically trained authors made clinically relevant decisions in their predictive CDSS design process but did not describe it in their article. Of the 55 articles that did not mention any clinician involvement, 39 (71%) were authored by at least 1 person with a health-related affiliation (eg, MD in title, located at school of nursing),[29,30,46,50–54,56–58,60,62,63,65–71,74,76,78,79,81,82,84–86,90–92,95,96,100,103–105] 14 (25%) were not authored by investigators with health-related affiliations,[47–49,55,61,64,72,73,75,77,80,87–89] and 2 studies did not report affiliation.[59,83]

DISCUSSION

The results of this scoping review indicate that clinical expert involvement is most prevalent in the specification and integration into environment stages of predictive CDSS design for nurses and providers in the hospital. Clinical expert involvement was less prevalent in the intermediary stages of predictive CDSS design (Table 3, Figure 2). This is not entirely surprising, especially for articles describing machine learning model development—as clinician involvement in machine learning is likely not considered customary; clinicians are not standardly trained in machine learning. However, recent literature on improving the understandability of machine learning models describe involving domain experts in development, particularly for verifying and increasing clinical relevance or correctness

and for feature selection.[13,65,106,107] However, with only 21% (n = 16) of studies on component development involving clinical experts for verifying clinical relevance or correctness or for feature selection, our findings indicate that this is not widespread practice. We note that using clinical expertise for feature selection is not necessarily state of the art. However, recent literature illustrates creative ways that expert knowledge can be integrated with computational feature selection.[106,108] For example, Boulet et al[106] used a power prior to incorporate numerical clinical relevance weights assigned by clinical experts with stochastic search variable selection.

Notably, 17 studies described in this review used the publicly available MIMIC (Medical Information Mart for Intensive Care) datasets (Supplementary Table 3),[109,110] which has implications for clinical expert involvement, as the experts may be advising on EHR data derived outside of the institution and workflows with which they are most familiar.[111] Alternatively, clinical experts may serve to advise on public data generalizability.

By including studies across the stages of system design, our findings highlight where in the process predictive CDSS research is published. It is clear that evidence on implementations of predictive CDSS for nurses and providers in the hospital are lacking, as 90% of included studies are of, at most, the component development stage and no studies are of the routine use stage. This dearth may be a reflection of known adoption challenges,[10] the extensive resource and time investment required to implement predictive CDSS, or lack of evaluation research being conducted or published. The low prevalence of studies from the specification stage may indicate that most investigators evaluate the need for a predictive CDSS through literature review, rather than qualitative research, which is a valid approach.[15,16] However, if investigators are conducting research on component development in the absence of rigorous specification evaluations, they may struggle overcoming the known challenge of ensuring relevance to the clinical domain.[10] The 3 studies of the specification stage were published in the most recent year (2019), which may indicate that investigators are considering adoption challenges by working to thoroughly understanding the needs and desires of clinician end users from the outset, as has recently been recommended.[112]

Beyond universal CDSS adoption challenges outlined in foundational literature (eg, importance of human-computer interface)[113] and those described by Shortliffe and Sepúlveda,[10] Lenert et al[114] recently detailed another specific challenge that predictive CDSSs may face after implementation—model degradation if behavior change occurs. The authors suggest modeling the intervention space (eg, modeling antibiotic administration for sepsis CDSS) in development so that likely changes to the outcome distribution are learned. This is a unique challenge to predictive CDSS and certainly a potential area for clinician involvement not described in our review findings.

Predictive CDSS adoption also has implications for clinician reasoning. Clinicians must consider the merit and consequence of a data-driven prediction though they are accustomed to looking to EHR data for documented observations.[115,116] While we have reviewed one approach to easing adoption—involving clinicians in
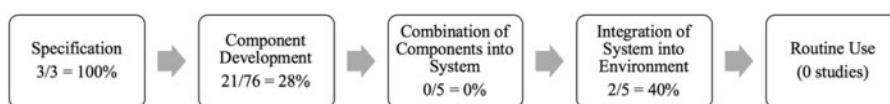

Figure 2. Prevalence of clinician involvement per stage of system design.

system research and development—new training programs are likely needed to equip clinicians with the skills needed to understand the strengths and limitations of predictive CDSS.[111]

Work done outside the hospital setting demonstrates the potential promise of clinical expert involvement.[106,108,117] Simon et al[117] described and advocated for engaging clinical experts across the stages of designing and implementing a predictive CDSS for oncology treatment, attributing the success and veracity of their predictive CDSS to this collaboration. Others have described clinician involvement in the development of a machine learning–based diagnostic decision support system, which clinicians co-designed by thinking aloud as they interacted with a model explanation interface.[118] Such efforts have the potential to overcome known challenges namely, increasing usability, clinical relevance, understandability, and delivering CDSS in a respectful manner.

Future directions

The structure and timing of this scoping review is optimal for informing future predictive CDSS research and development. First, the multitude of strategies for involving clinical experts in predictive CDSS research found in this review should be empirically evaluated. One approach may be to measure clinician end-user adoption of or trust in implemented systems. Alternatively, researchers may compare using clinical expertise in any of the ways described (eg, feature selection, verifying clinical relevance or correctness) with taking a purely computational approach or relying on nonclinical developers. Outcomes may be simple comparisons of model accuracy or more long-term evaluations of later stages of design. Aptly, informaticians are calling for a shift in focus away from the mechanics of predictive modeling toward the sustained benefit of predictive systems in practice.[21] As such, clinician involvement in predictive CDSS research should be evaluated according to the value added to patient care and clinician workflows.

Second, the lack of studies reporting on implemented systems indicates these findings may inform future implementations and that this is an area of needed research. Those planning a predictive CDSS implementation should review and consider the merit of using the methods for clinician involvement described in this review. We also suggest investigations of evidence-based implementation strategies, such as Expert Recommendations for Implementing Change[119] or evaluating implementation success according to a validated framework such as RE-AIM.[120]

Third, we advise that future publications of predictive CDSS research standardly report clinician involvement explicitly. Interpretation of our findings should consider that this is not yet standard practice and authors may have omitted detail on clinician involvement. However, because machine learning is burgeoning in the healthcare domain, there is an opportunity to institute standard reporting guidelines, including description of clinical expert involvement. There is a recent call to expand the TRIPOD (Transparent Reporting of Multivariable Prediction Model for Individual Prognosis or Diagnosis) checklist (criteria for reporting findings from development or validation of medical prediction models) to better suit machine learning, as the original was created primarily for regression models.[121] The panel convened to expand the TRIPOD checklist may use these findings to consider the relevance of incorporating guidelines on reporting clinician involvement.

Finally, these findings show that predictive CDSS for nurses and for clinical specialties outside of intensive care are underrepresented. Many of the included studies modeled outcomes that nursing care certainly impacts (eg, sepsis, in-hospital mortality) but do not all name nurses as target end users. Additionally, 46% of reviewed systems were developed for adult ICUs, pointing to opportunities for research in less represented (eg, pediatrics) and unrepresented (eg, orthopedics) specialties. We suggest a follow-up review in a few years to illuminate the progression of research on predictive CDSS with regard to methods, implementation, and variety of target users and specialties.

LIMITATIONS

In consideration of feasibility, relevant journals were not hand-searched and additional databases were not queried, potentially limiting the number of eligible studies located. We attempted to mitigate this by strategically selecting popular databases and including conference proceedings. Additionally, our analysis was restricted to the scope of Stead et al's[15] framework of system design; thus, we could not comment on clinician involvement in work outside of the stages, for example, curation of datasets. Finally, our review search did identify CDSSs that are further along in stage of development but were excluded because they exclusively used logistic regression.[122,123] While not covered here, lessons from their implementations should be considered in the discourse of mitigating challenges to predictive CDSS adoption.

CONCLUSION

This scoping review found clinical expert involvement in predictive CDSS research for the hospital most prevalent at the specification and integration into environment stages. However, most published research is of the component development stage, where clinician involvement is less prevalent but has been proposed as a method for mitigating challenges to adoption. Further empirical research is needed to understand the impact of involving clinical experts throughout the predictive CDSS design process.

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AUTHOR CONTRIBUTIONS

JMS and KDC conceptualized the review and NE and SCR advised on the scope. JMS, KDC, and AJM conducted the title/abstract screening. JMS and KDC conducted full text screening. JMS conducted data extraction. KDC verified extracted data. JMS drafted the manuscript with revisions and feedback from AJM, SCR, NE, and KDC.

SUPPLEMENTARY MATERIAL

Supplementary material is available at *Journal of the American Medical Informatics Association* online

DATA AVAILABILITY

There are no new data associated with this article.

CONFLICT OF INTEREST STATEMENT

The authors declare no competing interests with respect to this publication.

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