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Using Data-driven Clinical Decision Support to Integrate Precision Cancer Symptom Management Into the Electronic Health Record

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ABSTRACT

Objectives: Electronic patient-reported outcome measures (ePROs) are being implemented in clinical care to monitor symptoms in patients with cancer. Although the use of these measures is associated with improved outcomes, challenges remain with integrating ePROs into the workflow due to burdensome training and unclear roles for who will manage uncontrolled symptoms. The use of clinical decision support (CDS) can mitigate these challenges. This article discusses the use of CDS, the integration of CDS into the electronic health record (EHR), lessons learned, and future directions.

Methods: The Sapphire Cancer Symptom Management CDS system is used to illustrate the development, integration, and testing of CDS in the EHR. A team of experts designed this system based on previous experience and research literature. The discussion synthesizes peer-reviewed literature, expert opinion, systematic reviews, and meta-analysis as sources of data.

Results: Symptom management algorithms were created for nine cancer symptoms and then programmed into the CDS platform and integrated into the EHR. Integration involved using innovative technologies, which included application programming interfaces and interoperable data standards, to integrate the system into the EHR. Relevant EHR and patient-reported data were used to generate individually tailored symptom management recommendations. Testing of the system was accomplished using test patients that reflected real-world patient experiences. We found that the data needed for the algorithms were complex and some elements were not readily available in the EHR. Having clinicians verify a few critical elements assured accuracy and safety of the recommendations.

Conclusion: Innovative technologies enabled the integration of CDS into the EHR and the generation of individually tailored cancer symptom management recommendations. Future testing is needed to evaluate whether the use of CDS improves patient outcomes.

Implications for Nursing Practice: CDS has the potential to improve guideline-concordant symptom management and facilitate supportive care referrals at the point-of-care to improve clinical care.

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Uncontrolled symptoms impose a significant burden for adults undergoing cancer treatment and are associated with increased emotional distress, deceased physical function, social function, and survival.[1-4] Patients often experience multiple symptoms that change over the course of time and vary with cancer treatments. The prevalence of >3 moderate to severe symptoms varied from 27% to 47% in 3,106 ambulatory patients with breast, prostate, colorectal, or lung cancer.[5] Similarly, another study evaluated the co-occurrence of >3 moderate to severe symptoms among 31,866 ambulatory patients in a medical oncology setting and found the frequency varied from 45% to 67%.[6]

Given that adequate symptom management is one of the cornerstones for quality cancer care, electronic patient-reported outcome measures (ePROs) to monitor symptoms are increasingly used in routine cancer care to improve communication, decrease symptom severity, enhance treatment adherence, and reduce emergency room visits, hospitalizations, and care costs.[7-10] Current ePRO systems primarily offer web-based self-management tools for patients and/or symptom alerts to notify staff when patients experience increased symptom severity levels.[11-13] Challenges with incorporating these systems into cancer care delivery have included inadequate

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Layperson Summary

What we investigated and why

Adults with cancer are reporting their symptoms into questionnaires in their Smart phones or computers. These "electronic patient-reported outcome measures" are used to monitor cancer symptoms. Routine use of these measures is difficult because nurses who receive these reports may not be the clinician who has been assigned to manage them. Adding what is called "clinical decision support" (CDS) solves this problem. CDS tools are electronic resources to help clinicians provide management of patient symptoms based on national guidelines. This paper discusses CDS that was integrated into the electronic health record (EHR) to make symptom management easier for patients and their clinicians.

How we did our work

A team of experts designed a CDS system for cancer symptom management. This system used new tools that made it possible to integrate CDS into the EHR. The CDS made suggestions for further assessment and treatment of each symptom and presented these to the clinician to aide them in their management choices. The suggestions made by the CDS were tested for accuracy and were found to be acceptable.

What we found

We combined patient-reported and EHR data to generate recommendations to manage cancer symptoms. We found that the data needed to create the recommendations was complex and some elements were not available in the EHR. We were able to find solutions to the problems and improve the safe use of CDS.

What it means

Our work shows that CDS can be integrated into the EHR, and there is adequate data from patients and their records to provide recommendations to clinicians to improve their ability to manage cancer symptoms. Future testing of CDS will determine whether the use of this technology can improve patient outcomes.

workflow integration, burdensome training for nurses, and unclear roles for who will take responsibility for following up to provide symptom management.[11] "Alert fatigue" has become a particular concern, where frequent alerts desensitize clinicians, delaying responses to adequate follow-up. Mazza et al.[14] reported that 34% of weekly symptom surveys from 539 patients generated alerts. Another study[15] on 178 breast cancer patients showed that of 1,087 surveys, 36% reported severe symptoms, for which only 77% received follow-up within 48 hours. Response time to follow-up did not vary significantly by symptom severity or disease stage.

More effective approaches, such as the use of clinical decision support systems (CDS) along with ePROs, are needed to improve timely care, reduce staff burden, and provide evidence-based symptom management. This article provides an overview of CDS systems and uses the Sapphire Cancer Symptom Management Clinical Decision Support System as an exemplar to illustrate how an algorithm-based CDS was developed, tested, and integrated into the electronic health record at two comprehensive cancer centers. We describe, herein, the lessons learned from this experience and future directions for CDS systems to support the evidence-based management of patients' symptoms in healthcare delivery systems.

Overview of Clinical Decision Support

Clinical practice guidelines are available to inform management of cancer-related symptoms[16-22] but are not applied consistently in care delivery.[23,24] The use of CDS systems may help disseminate clinical guidelines into care, improve management of uncontrolled symptoms, and facilitate referral to supportive care services.[25] CDS is defined as computerized programs providing clinicians with person-specific information that is intelligently filtered and presented at the appropriate time to enhance health care.[26] Computerized alerts, reminders, condition-specific order sets, documentation templates, and clinical guidelines are different types of CDS interventions that can be implemented within the electronic health record (EHR). Effective CDS systems have well known properties: they provide actionable recommendations in addition to clinical assessments, are delivered within the operational workflows, specifically at the time and location of decision-making, and include ongoing support that evolves over the course of a patient's care.[27] CDS has been found to improve guideline adherence, the patient-centeredness of care, and improves the consistency of care delivery processes across a variety of patient conditions including oncology, diabetes, renal disease, hypertension, cardiovascular risk reduction and depression.[28-34]

Overview of the Sapphire Cancer Symptom Management Clinical Decision Support System

Elimu Informatics and experts from Dana-Farber Cancer Institute and Medical University of South Carolina implemented an EHR-integrated CDS system to facilitate evidence-based cancer symptom management by clinicians at the point-of-care in two test environments. This system combined patient-contributed data about symptom severity and context with EHR data on clinical treatments, generating detailed, patient-tailored, actionable, pharmacologic and nonpharmacologic recommendations. In this section we describe an overview of the design and function of this CDS system for management of cancer symptoms, known as CDS-Sx (Clinical Decision Support for Symptoms). Table 1 provides a glossary of health informatics terms that may not be familiar to readers.

A team of CDS and clinical domain experts were assembled to design a fully electronic, EHR-integrated, interoperable CDS system for cancer symptom management, creating a standards-based specification for an application that would directly engage patients for data collection and integrate into the workflow of the EHR. The design process was informed by our previous experience in creating a CDS cancer symptom management system, research literature, and pragmatic experience of the expert team.[35-39] The use of the Fast Healthcare Interoperability Resource (FHIR) standard enabled interoperable interaction and data exchange between the symptom management application and the EHR, and the Substitutable Medical Applications, Reusable Technologies (SMART) on FHIR standard, in combination with the Clinical Decision Support Hooks standard (CDS-Hooks),[40] allowed for direct integration of the application into the EHR for use in clinical care.

The CDS-Sx system is comprised of the Sapphire cancer symptom management system, a patient-facing application (patient app), and a clinician-facing application (clinician app). Sapphire is a cloud-based development platform that is aligned with the latest standards designed to promote interoperability, data consistency, and safe practices (Table 2). It is designed for use with a wide range of symptoms, cancers, and chemotherapies and comes with pre-built widgets (i.e., problems, medications, calculators) that can be used in varied configurations to assemble apps for a rapid development process for new treatment contexts. The patient app collects information about symptom severity using self-reported ePRO measures[41-44] (Fig. 1). Additional contextual information is collected if patients endorse symptoms that pass a severity threshold of moderate or higher. In

TABLE 1
Glossary of Health Informatic Terms

Term	Definition
Technical integration	CDS-Sx was connected to the EHR Epic test environment in two cancer centers. This process allowed the systems to work together and share data.
Fast Healthcare Interoperability Resources (FHIR)	FHIR is an interoperable HL7 standard with application programming interface to enable exchange of electronic healthcare information across different systems.
Substituable Medical Applications, Reusable Technologies (SMART)	SMART on FHIR is an interoperable data standard that enables applications to access information in electronic heath record systems and allows external applications to appear as part of the EHR.
Drools	Open-source software that offers a Business Rules Management System (BRMS) for creating forward and backward chaining production rules. The Drools workbench provides a core Business Rules Engine (BRE), a web authoring and rules management application.
Application Programming Interface (API)	API employs predefined standards to create a system-to-system interface that allows software programs to communicate with each other and to exchange data. Unlike a user interface an API is not visible to users
Interoperability	Ability of different health information systems, devices and applications to access, exchange, integrate and cooperatively use data in a coordinated way
App	Self-contained computer program that allows users to perform specific tasks on a mobile or desktop device. Apps are pre-installed on the device, distributed via a proprietary app store, or accessed through a Universal Resource Locator (URL) link.
mCODE	Consists of approximately 40 FHIR profiles related to cancer care organized into 6 thematic groups: patient information, disease characteristics, health assessment, genomics, cancer treatment and outcomes

this case, additional information such as symptom characteristics (e.g., somatic or neuropathic pain), patterns (e.g., constant or intermittent pain), comorbidities (e.g., peptic ulcer disease), and remedies tried (e.g., opioids) are collected directly from patients, that, in turn, inform the symptom management algorithm. The clinician app provides a dashboard displaying an overview of the patient-reported level of symptom severity for each symptom using red, yellow, and/or green indicators to reflect symptom severity and a graph of historical symptom severity over the past three months (Fig. 2). From this dashboard, clinicians can choose which symptoms to actively manage. To ensure patient safety, clinicians must review critical data elements that could cause potential harm if incorrect, before generating the evidence-based clinical recommendations that were explicitly tailored to the needs of each individual patient. Our guiding heuristic was to minimize clinician burden while providing a mission critical checklist of monitoring tasks. Experts identified up to seven "review-required" data elements for each symptom to inform a recommendation algorithm. In addition to the symptom management recommendations, symptom management documentation, billing codes for symptom management, and patient educational materials, were also generated to facilitate implementation of the recommendations.

TABLE 2
Health Informatics Standards

Type of Standard	Definition
Terminology Standard	These standards allow for the use of consistent, clearly defined terms that are combined to create healthcare code sets and classification systems such as ICD (International Classification of Diseases) for diagnoses, CPT (Current Procedural Terminology) for procedures, SNOMED Clinical Terms for clinical concepts, LOINC (Logical Observation Identifiers Names and Codes) for lab observations, and RxNorm for clinical drugs.
Data Transport Standard	These standards facilitate transmission of data between different health systems. They define the format, document architecture, data elements and application programming interfaces to use in data exchange. Health level 7 (HL7) is a set of standards for exchanging health information.
Privacy and Security Standards	These standards establish administrative and technical rules for protecting sensitive health data from misuse, unauthorized access or disclosure. The Health Insurance Portability and Accountability Act (HIPAA) security rule designates national standards to protect an individual's electronic personal health information

Fig. 3 provides a composite view of CDS-Sx that includes system components, data sources, workflow, and individuals interacting with the system. The first step in developing the CDS-Sx system was to create symptom management algorithms for nine common symptoms experienced by adults undergoing cancer treatment, which included fatigue, constipation, diarrhea, nausea/vomiting, pain, insomnia, depression, anxiety, and skin toxicity. Comprehensive symptom management algorithms were created by convening panels of subject domain experts. A literature review, which included identification of national and international clinical practice guidelines, and creation of tables for review of the data was compiled by the research staff.[16-22,45,46] A draft algorithm flow diagram was created so that the subject domain experts could refine the content. As a final step, the symptom management algorithms were vetted with oncology end-users at academic and community cancer centers.[39] Each algorithm was then transferred to informaticians and computer programmers who converted the algorithm into computable logic and created the value sets to interpret data used in the algorithm logic (Fig. 3A).

The next step engaged patients in the symptom management process through the collection of patient-contributed health information. Expert clinicians defined rules for identifying patients who should be invited to complete a symptom assessment questionnaire 24-48 hours before a scheduled oncology clinic encounter. These rules were encoded into patient enrollment logic that was used to analyze a daily feed of clinic schedule information to identify patients who met the specified criteria. CDS-Sx then sent a text message to these patients inviting them to complete a questionnaire and providing an encrypted Universal Resource Locator (URL) link through which the questionnaire can be accessed using a web browser on a smartphone (Fig. 3B).

The patient then opened the questionnaire that presents the patient-reported outcome measure survey questions to assess symptom severity across nine commonly occurring symptoms. If a patient has moderate or greater severity of a symptom, the patient is asked to respond to detail questions to learn more about the characteristics of the symptom and any remedies that the patient may have already initiated. These detail questions were derived from the patient-focused information that is required to inform the symptom management algorithms. The data elements restricted to the data requirements of the symptom management algorithms were extracted from

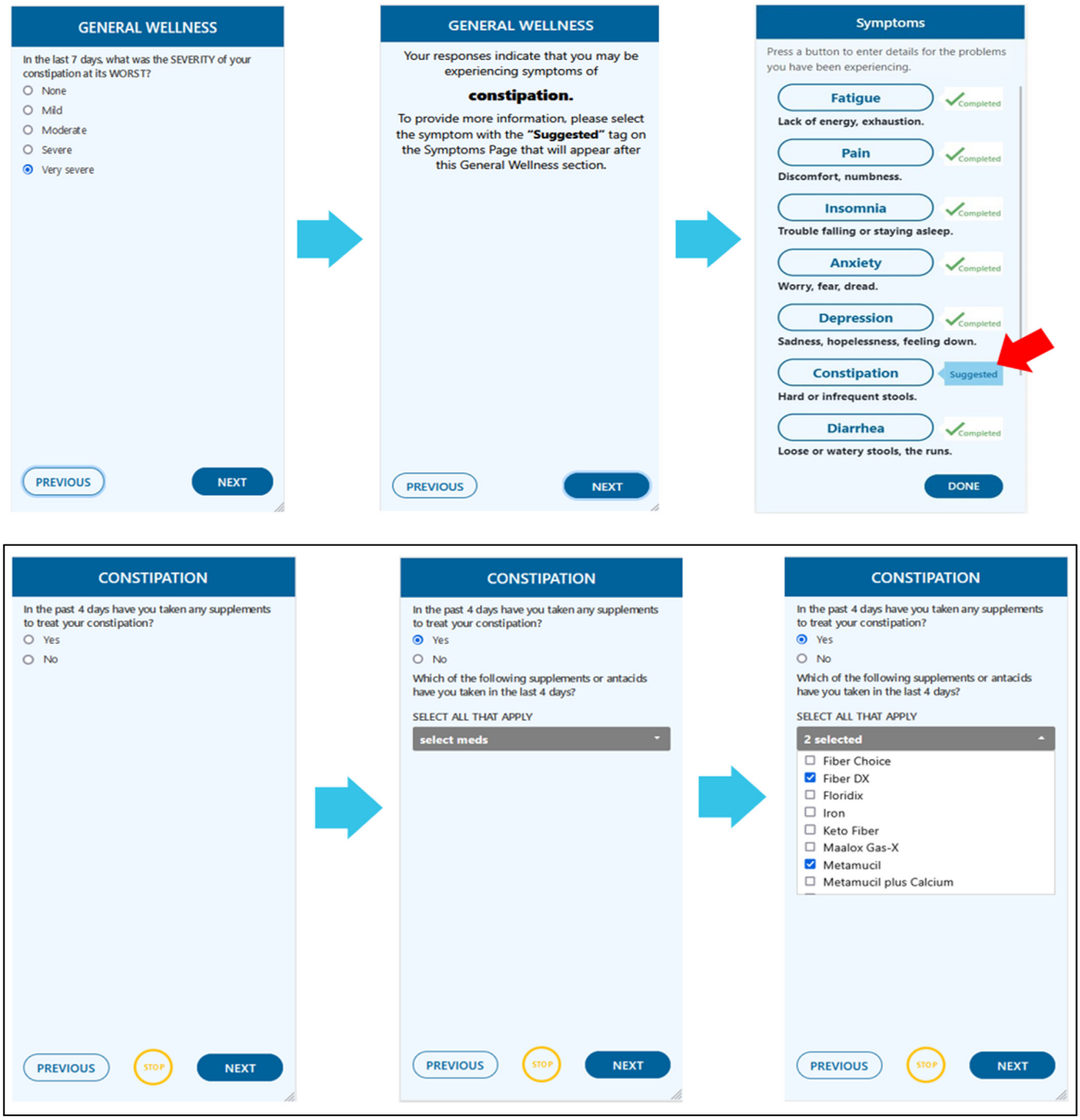


FIG. 1. Patient app symptom assessment questions.

the patient's EHR using the FHIR application programming interface (API) standard. Patient-generated health data and EHR data can be added directly to the symptom-specific dataset or can be combined and processed through an inference engine to draw conclusions from the data that inform the tailored symptom management recommendations (Fig. 3C).

The last step in the recommendation generating process focuses on the gears in the diagram (Fig. 3D) that represent the clinical decision support data processing engine. This engine imports the symptom specific dataset and uses the value sets to interpret these data to run the data through the computable logic to instantiate a specific symptom management logic pathway for the patient that is attuned to the patient's context and health status. The process of traversing this logic pathway identified the appropriate care *recommendations* for the patient. The following sections will discuss how the symptom management algorithms were converted to a computable format, the type and sources of data needed to generate the patient-specific recommendations, and the lessons learned from the technical integration of CDS-Sx into the two Epic EHR test environments.

Conversion of Symptom Management Algorithms to Computable Format

The conversion of the symptom management algorithms into a computable format was initiated by creating rules that combined information collected from patients and data extracted from the EHR to generate inferences about a specific clinical concept. A sample

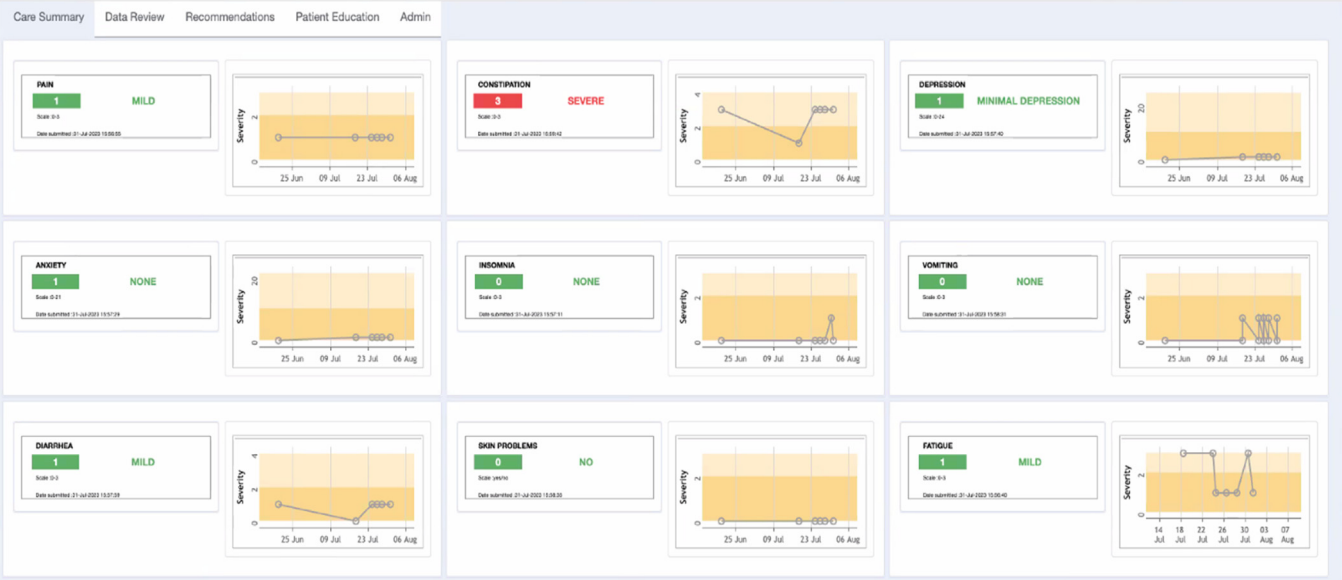


FIG. 2. Clinician app: Dashboard.

inference concept was the detection of risk for unsupervised exercise, which would influence the type of exercise recommended for a patient with fatigue by combining patient-reported information about fall risk and EHR-provided data to detect thrombocytopenia. We then created a series of rules using a Business Rules Management System (BRMS) open-source solution known as Drools (www.drools.org) that used inference-derived concepts, patient-generated health information, and original EHR data to replicate the decision logic encapsulated in the symptom management algorithm flowsheet.[47] The pathway through nodes created by the decision logic determined which recommendations would be provided for a specific patient case. We created dozens of value sets including conditions, procedures, medications, allergies, and observations (primarily laboratory results) to enable the BRMS to interpret EHR data used in the inferencing and logic rules.

Whenever possible, variables and value sets were reused across rules. Hundreds of logic rules and value sets were created to computerize all 9 symptom algorithms. These value sets not only served to identify and interpret data from FHIR resources but also to determine which EHR data elements were appropriate to display for the data review tab for each symptom. We posted the hundreds of value sets that represented the concepts across all 9 algorithms to our terminology server for reference by the decision logic.

Identifying and Accommodating EHR Source Data

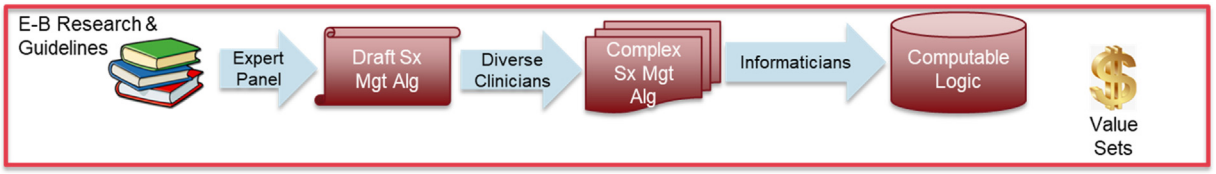
The clinician app was designed to consume information reported by patients through the patient app questionnaire and data from the patient's EHR accessed through FHIR APIs along with combinations of these two data sources produced through logical inferences. A reference list of all data elements used across all nine algorithms was created and our technical integration partners identified the sources for the needed data elements (Table 3).

Accessing most of the required EHR data was straightforward for categories such as conditions (problems) and observations (laboratory results). However, procedures were not stored in the EHR in a consistent format that could readily be consumed by the clinician app. Since procedures were a critical component of the logic for several of the symptom algorithms, we identified alternative resources through which to obtain procedure information including the FHIR Procedure, Encounter, and ExplanationOfBenefit Resources (a Resource is a standards-defined list of attributes that characterized a specific type of data). Obtaining data related to the intensity and duration of radiation therapies was particularly challenging since radiation treatment data are complex and were maintained in electronic record systems external to the primary EHR at both of our technical integration partner sites. Since radiation therapy data may be missing, we ended up relying on a key component of our system design—namely, a clinical data review process through which a clinician can adjust inference interpretations to correctly indicate the presence or absence of radiation treatments for a specific patient case. While prescribed medications were relatively straightforward as a data source through the FHIR Medication resource, chemotherapy data were more difficult to obtain. Chemotherapy information was stored in treatment plans within the EHR. Chemotherapy medications only appeared in the medications list (where they can be incorporated into the FHIR Medication resource) after a chemotherapy treatment session had been signed off as completed. For ongoing therapy plans, the chemotherapy medications may not be available. Once again, the clinician data review process provided the additional data needed to ensure that the correct chemotherapy information was submitted to the decision support rules engine.

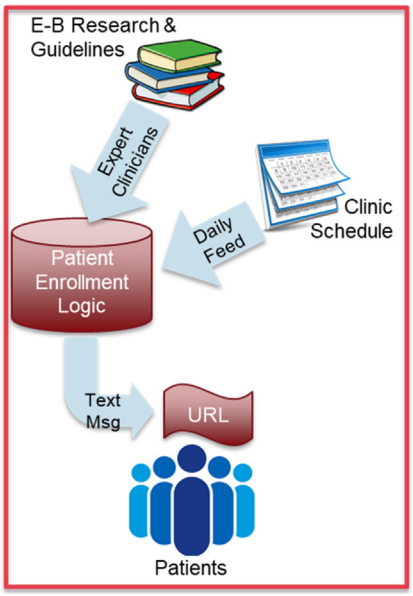
Integration and Testing of the Cancer Symptom Management CDS System

The CDS-Sx system was integrated into the test environments of the Epic EHRs at two comprehensive cancer centers. Integration involved using FHIR APIs to obtain the data required to run the symptom management decision logic from the EHR and SMART on FHIR to integrate the system into the EHR. The relevant EHR data and the patient-contributed data were stored on a secure external HIPAA-compliant server hosted through Amazon Web Services. These data were incorporated into a symptom-specific data set for use by the inference engine and the symptom management logic.

To assess the performance of the system, expert clinicians created nine sample test patients each with high severity of one symptom that reflected real-world patient experiences. For each use case we assessed the overall performance of the system in terms of the accurate display of symptom severity data and EHR data, and the correct derivation of inference results and final recommendations. We also confirmed availability of correct billing support information, educational resource information for clinicians, and patient educational information. We found that the average for overall correctness of the



(A)



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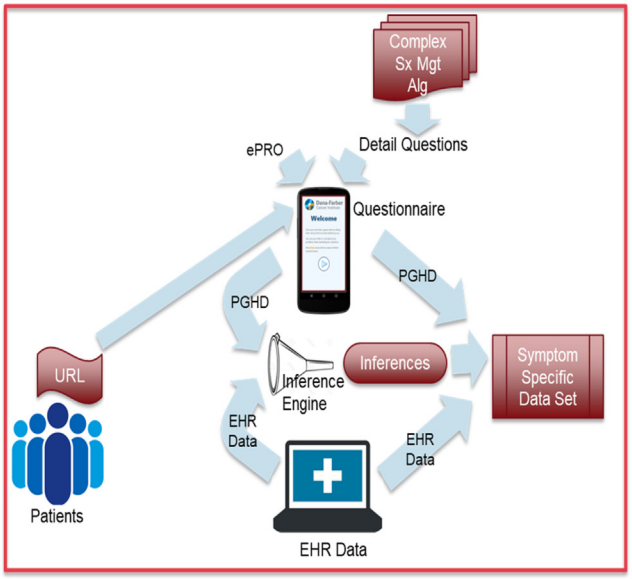

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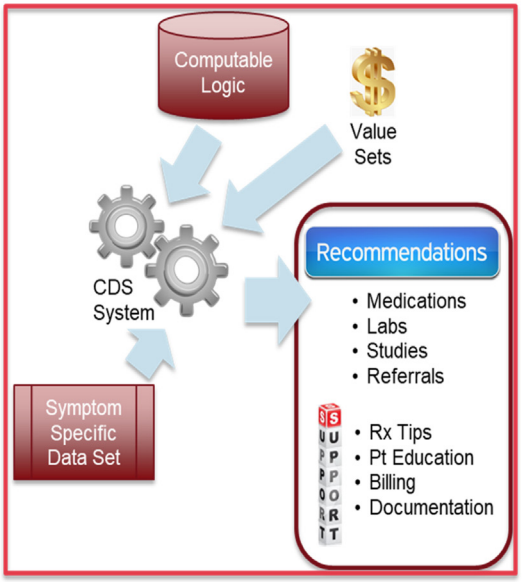

(D)

FIG. 3. Overview of the CDS-Sx system. A, Translate guidelines into rule-based algorithms. B, Send patients a link for data collection. C, Collect patient-generated health and EHR data. D, CDS engine generates tailored recommendations.

system for the two sites was between 88%-90%. Four components of CDS-Sx performed with 100% consistency. These components included the accurate display of patient symptom severity, presentation of symptom-related conditions to support billing, provision of "helpful information" for clinicians, and presentation of resources for patient education. The display of EHR data was more problematic with significant difficulties displaying procedures (0%) and cancer therapies (68%-74%). The display of relevant comorbid conditions was mostly successful at a level of 95%, followed by non-cancer-related medications at 83%, and laboratory results between 78%-83%. On the logic side, inferences were correct in 86%-91% of cases whereas recommendations were correct in 75%-79% of cases.

Table 3
EHR Data Types and Sources

Data Element	FHIR Data Resource APIs
• Pending appointment information by location over defined date range (include appointment location, type, provider, patient name, appointment date, appointment time, appointment duration)	Appointment
• Conditions/problems/diagnoses	Condition
• Procedures (if surgery, chemotherapy, or radiotherapy treatments are available via other APIs, then access to those data elements also is needed).	Procedure Encounter Explanation Of Benefits ServiceRequest Claims Coverage
• Medications	Medication Request Medication Statement Care Plan ServiceRequest Medication
• Allergies	Allergy Intolerance
• Observations (including weight, height, lab results)	Observation
• Study results	Diagnostic Report
• Patient demographics (patient name, gender, ID, date of birth, email address)	Patient
• ePRO	Questionnaire Response

Lessons Learned From the Technical Integrations

The two technical integrations of CDS-Sx provided valuable insight into what will be required to use CDS-Sx at a production level. Several lessons were learned from this experience that can guide future development and implementation initiatives. First, developing an EHR-interoperable CDS-Sx was more complex than we had anticipated, despite our prior experience with developing a stand-alone decision support system for cancer symptom management. This increased complexity arose from collecting and using more patient-generated heath data, addressing a greater number of symptoms, several of which had unique requirements, and detailed symptom management logic that considered dozens of parameters to generate contextually relevant, patient-appropriate, detailed care recommendations.

Second, managing the decision-making infrastructure was more difficult than expected. This difficulty arose in part because of the increased complexity of the data required to inform the algorithms and from the underlying knowledge required to support the decision logic. We created 240 value sets for the project representing conditions, medications, procedures, laboratory tests, and observations to interpret the data elements used for generating inferences and recommendations (Table 3). Several of the logic statements considered five or more parameters simultaneously to identify the correct recommendation for a given patient situation.

Third, the availability of EHR data through FHIR resources was variable across the Epic installations and some resources were not populated with data. The coded representation of procedures in the EHR was inconsistent and often delayed. Planned chemotherapy medications were not available through the Medication FHIR resource until they had been “released” by the clinician authorizing the administration of the pharmaceutical. Data reflecting radiation therapy was not included in the oncology module of Epic. Furthermore, some datatypes in Epic were associated with proprietary codes as opposed to codes from standard vocabularies.

Finally, in future development efforts it will be important to carefully consider the elements that are absolutely required to inform CDS and not burden patients and their clinicians, Tradeoffs are necessary to balance the requirements needed for specificity of the care recommendation versus the burden of data collection.

Future Directions for Enhancing Use of CDS in the EHR

The next step for optimizing performance and integration of CDS systems into the EHR is to explore how to leverage the use of artificial intelligence (AI) technologies. The advantage of AI is that these technologies can synthesize large amounts of complicated and disparate data quickly and can then parse, learn from and/or make informed decisions.[48] Although AI has been used most often to assist in diagnostic and therapeutic decisions in oncology, applications to enhance CDS systems are emerging.[48-50] There are several key areas within the context of ePRO and symptom management CDS systems that have the potential to benefit from the use of AI which include 1) using unstructured data within the EHR, 2) streamlining approaches to update guideline-based information needed to inform CDS recommendations, 3) using clinician supervised generative AI methods to assist with augmenting the creation of rule-based CDS, and 4) incorporating predictive analytics to identify individuals at high-risk for treatment-related side effects and initiate preemptive interventions.

Eighty percent of EHR data is in unstructured documents making utilization of these data difficult[51.] New EHR and AI technologies are emerging that promise to support efficient capture of real-world data that can be used to support CDS systems.[48,51-54] The use of natural language processing (NLP), a type of machine learning, may be particularly useful to extract information from text in clinical notes for automated data collection.[54] An active area of research and important application for NLP that has the potential to be transformative to clinical care is to be able to extract patient self-reported symptoms from clinician notes that can be used to enhance the reach of CDS symptom management systems.[53,55-58] As ePRO’s are increasingly integrated into health care systems, disparities in care may be exacerbated due to a lack of digital literacy among varied groups of patients[59] impacting their participation in e-surveys on websites or their use of smartphone apps. Two recent studies found that patient engagement in remote symptom monitoring programs varied among groups of adults with cancer. In a secondary analysis of a remote symptom monitoring program, Rocque and colleagues[60] identified that Black adults with cancer and individuals living in more disadvantaged neighborhoods were at risk for lower engagement in the program. In another study, Cancel and colleagues[61] assessed the feasibility of collecting ePRO data in a remote symptom monitoring program for adults aged 75 years and older with cancer. The results from Cancel et al.’s study demonstrated a limited feasibility rate (26%) of ePRO data collection, mainly due to lack of Internet access.

One challenge with CDS systems that incorporate evidence-based guidelines to provide clinical practice recommendations is being able to maintain and update the systems on an ongoing basis to keep current with the latest evidence. To meet this need, the use of AI has been explored to promote clinical practice guideline implementation.[62] A variety of AI technologies, including pattern-based machine learning algorithms and large language models, have been used to assist in retrieval of articles, synthesis and summary of clinical evidence to make the process of updating the literature more efficient.[62-64] There is still a gap in the ability to automate the creation and translation of the clinical algorithms into a computable format due to the complexity of the tasks.[62]

Clinician-supervised AI could augment the creation of rules-based CDS in practical and safe ways. For example, there are over 240 value sets and a large number of rules supporting CDS-Sx that today require informaticians to interact with the rules to make clinical choices. AI can potentially assist in two ways (1) augmenting the knowledge curation process and (2) retrieving insights from clinical data. AI can augment knowledge curation by helping to create value sets and by providing translation from guidelines to candidate rules that can be reviewed and finalized by clinicians and informaticians. This AI-supported curation can potentially save much time. Elimu Informatics has been exploring the use of this approach with

promising results (personal communication, Dr. James Shalaby, CEO, Elimu Informatics, 4/4/2025). In addition, AI could mine patients' health records to retrieve responses to questions that serve as the evidence driving the algorithms. For example, AI could potentially identify the tried and failed classes of laxatives to treat constipation in the context of high-risk patients and/or whether the patients have had procedures that would require avoidance of the gastrointestinal stimulant laxative classes. Today that information is difficult to mine out of the EHR by just using drug codes correlated to dates when certain procedures may have been performed.

Advances have been made in being able to use EHR data to identify those at high-risk for adverse events, including prediction rates for 30-day readmission rates, in-hospital mortality, length of stay and future symptoms associated with cancer treatment.[65,66] A recent study by Chae and colleagues[67] has shown the ability to use EHR data to predict symptom severity and progression across chemotherapy treatment trajectories in adults with cancer that would allow preemptive treatment planning to individualize symptom management. Other studies have shown promise in using machine learning approaches to predict cancer pain related outcomes, those at risk for depression, and identification of hospitalized adults with uncontrolled symptoms (pain, dyspnea, nausea and vomiting) who would benefit from referral to early palliative care.[68-70]

Although AI technologies hold promise in supporting the use of advanced CDS to improve symptom outcomes, they are still in the early stages of development. Many AI systems function as a "black box" for which the rationale behind recommendations is not transparent and may vary based on the knowledge used to generate recommendations. Both issues are concerning problems relative to the consistency and precision required for clinical care guidance. In addition, most AI systems are prone to contrived errors, known as confabulation or hallucination, based on the process through which knowledge sources were combined for a given scenario. Other issues also need to be addressed to be able to optimize AI use across health systems. A few of these challenges include the need to standardize data collection, technical issues to ensure unbiased recommendations, and reporting of methodologies to allow replication. To optimize the use of these technologies, standardized data collection methods and support for interoperability will be needed so that larger data sets can be created. Initiatives to standardize data collection, such as the minimum Common Oncology Data Elements (mCODE) are underway.[48,71] However, this initiative does not address the standardization of ePRO measures. An important avenue for future advancement of symptom management would be to create common data elements, and logical observation identifier and name codes (LOINC), for collection of ePRO data. A technical concern that arises related to the use of AI technology to generate rules for decision support is that there may be algorithmic biases due to having non-representative data, poor quality data, or having an insufficient quantity of data in the training data set that may result in outdated or irrelevant recommendations.[48] A systematic review and analysis of machine learning models that included ePRO data in oncology found that only 17% of the studies presented a discussion of the clinical applicability of the developed model and 5.8% provided a code to reproduce the model and results highlighting the need for improved reporting and utility of future use.[72]

Conclusion

The incorporation of ePRO and CDS systems driven by patient specific data into the EHR offers the potential to improve the precision, accessibility, ease of use, and adherence to guideline-based care. Advances in technology, along with health policy changes, have created an ideal environment for optimizing the performance of these systems, driven by demands from payers, accrediting bodies, and professional organizations for high-quality, cost-efficient, patient-centered cancer care.[73-75] The integration of CDS into the EHR of health care systems allows access to a greater amount of patient-specific data that can be used to provide more context specific recommendations tailored to the individual patient. Future testing of CDS to evaluate the impact on patient outcomes is warranted.

Declaration of competing interest

Cooley, Lenert and Abrahm have no conflict of interest. Lobach and Elimu Informatics Inc. have a patent on the clinical decision support. Funding was provided through the National Cancer Institute.

CRediT authorship contribution statement

Mary E. Cooley: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Conceptualization. **Leslie A. Lenert:** Writing – review & editing, Supervision, Resources, Project administration, Methodology. **Janet L. Abrahm:** Writing – review & editing, Resources. **David F. Lobach:** Writing – review & editing, Writing – original draft, Supervision, Project administration, Methodology, Funding acquisition, Data curation, Conceptualization.

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