INTEGRATED CLINICAL DECISION SUPPORT:

ASSESSING OPPORTUNITIES AND OUTCOMES

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by

TIMOTHY A. GREEN

Dr. Chi-Ren Shyu, Dissertation Supervisor

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The undersigned, appointed by the dean of the Graduate School, have examined the dissertation entitled

INTEGRATED CLINICAL DECISION SUPPORT:

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presented by Timothy A. Green,

candidate for the degree of Doctor of Philosophy and hereby certify that, in their opinion, it is worthy of acceptance.

Dr. Chi-Ren Shyu

Dr. Jeffery Belden

Dr. Lori Popejoy

Dr. Stevan Whitt

DEDICATION

To my wife and son, who provided love, support, and encouragement and without whom this work would not be possible.

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ABSTRACT

Medical calculators play an important role as a component of specific clinical decision support (CDS) systems that synthesize measurable evidence and can introduce new medical guidelines and standards. Understanding the features of calculators is important for calculator adoption and clinical acceptance. Some medical calculators can fulfill the role of CDS for Meaningful Use purposes. However, there are barriers for clinicians to use medical calculators in practice. This research presents a novel classification system for medical calculators and explores clinician use and perceived usefulness of medical calculators. Additionally, we examine the effects of an EHR integrated decision support tool on management of pain in an inpatient setting. Metadata on 766 medical calculators implemented online were collected, analyzed, and categorized by their input types, method of presenting results, and advisory nature of those results. Reference rate, publication year, and availability of references were collected. We surveyed a population of resident and attending physicians at a medium-sized academic medical center to discover the prevalence of medical calculator use, how they were accessed, and what factors might influence their use, for example, EMR integration. We also conducted a retrospective evaluation of an EHR integrated CDS module focused on pain management, leveraging a novel approach to digital workflow evaluation within the EHR, focusing on patient-centric outcome measurements.

CHAPTER 1

1 Introduction

1.1 Clinical Decision Support Systems

The passage of the American Recovery and Reinvestment Act (ARRA) of 2009 [1] and the Patient Protection and Affordable Care Act of 2010 [2] had a tremendous impact on the adoption of electronic medical records (EMRs) within hospital systems, with adoption increasing more than fivefold since 2008[3]. The ARRA also brought Meaningful Use, whose core measures include provisions for the use and adoption of Clinical Decision Support (CDS) Systems in both Stage 1 and Stage 2 [4]. These rules were meant to introduce CDS into provider workflow in order to improve quality and patient outcomes. For these CDS systems to be effective, clinicians must input the data necessary to drive these systems. However, there are signs that clinicians are weary of the additional effort involved with EMR use[5–8]. Discrete data entered into EMRs hold promise for health informaticians[9], however, clinicians and patients have yet to fully recognize or benefit in systematically meaningful ways from their efforts[10,11].

In 2007, a report from the American Medical Informatics Association steering committee on CDS roadmap development released a report identifying three pillars for successful CDS adoption and use [12]: 1) Best Knowledge Available When Needed, 2) High Adoption and Effective Use, and 3) Continuous Improvement of Knowledge and Methods. The first pillar addresses workflow and integration, with a strategic objective to collect, organize, and distribute clinical knowledge and CDS interventions. The second pillar focuses on promoting adoption through a strategic objective geared towards supporting good CDS design and deployment best practices. The third pillar promotes continuous improvement through a strategic objective of leveraging EMR data to improve health management and enhance clinical knowledge.

A similar 2008 study by Sittig et al., identified a list of the top 10 grand challenges in CDS [13]. Two of the main themes identified in this 2008 study included a) improving the effectiveness of CDS, and b) the dissemination of existing CDS knowledge and interventions. Dissemination of new medical evidence has a well-known lag before acceptance into mainstream medical practice. Studies evaluating translational research lag suggests it can take 17 [14] to 24 [15] years for medical discoveries to enter mainstream practice. Recent innovations such as the SMART platform [16], the HL7 FHIR data interface [17], and CDS Hooks [18] are helping to drive the development of universal CDS that can plug in to multiple EMR systems. This should enable more rapid dissemination of new evidence-based medicine CDS tools.

1.2 Decision Support for Pain Management

Many CDS tools have been brought to bear on pain management [19], some dating back to 1972 [20], and yet the state of pain management is in crisis. The United States is in the middle of an opioid epidemic [21,22]. Over the course of the last decade, the American Pain Society, FDA, CDC, and JCAHO have released revised guidelines for the management and treatment of pain [23–27], yet proper pain control remains an elusive target [28,29], deaths from opioid overdose have reached unprecedented levels [30], and there is evidence to support a failure to properly manage opioid prescriptions for acute pain [31]. Current approaches for the development of CDS encompass attempts to find a combination of relevant clinical factors that can predict an outcome and therefore guide provider decision making [19]. Additional approaches to computer-based support for pain management include the computerization of decision trees that guide providers through predetermined protocols [32]. These rules based CDS are very effective at managing a patient population to a standardized protocol, however by design they are not intended to handle patients with contraindications to the protocol, thereby requiring a provider to override the recommendation. In the systematic review of clinical decision support by Pombo et al. [19], only 19% of the studies focused on treatment, and 32% were related to abdominal pain. Only one abdominal pain-related study reviewed for this paper published results related to patient outcomes, with many focused on accuracy of the system. The contribution of the proposed research is innovative because we will expand the understanding of the factors necessary to improve the adoption and effectiveness of CDS and validate a model of CDS focused on presenting pain-related clinical to data to a care team member from within the EHR.

1.3 Summary

Major themes identified by the prior research highlight the need for a thorough understanding of the implications of CDS deployment on workflow, integration, dissemination, and EMR data use. This research will expand the current state of medical calculator classification with an in-depth look at issues surrounding clinician workflow, automation, and delivery of evidence-based medicine, including medical calculator input and output modalities and reference availability. With this knowledge as a foundation, this research will then examine the effects that a CDS application that is appropriately integrated into the EHR can have on patient-centered outcomes.

The remainder of this dissertation is focused on expanding the understanding of factors necessary to improve the adoption and effectiveness of CDS and validating a model of CDS focused on presenting pain-related clinical to data to a care team member from within the EHR. Chapter two introduces a new taxonomy for describing medical calculators and analyzing those features specific to that form of CDS. Chapter three expands on this foundation by adding information on the use and perceived usefulness of medical calculators, their features, and barriers to use through a survey to practicing clinicians of various experience levels. In Chapter four we examine a specific use case of an EHR integrated CDS focused on pain management and its effects on patient related outcomes. Chapter five concludes with a summary of the key findings from chapters two through four, impacts on the present and future of clinical decision support, and describes future directions for research in the area of clinical decision support.

CHAPTER 2

2 A Taxonomy for Medical Calculators

The work in this chapter has been published in the proceedings of MEDINFO 2019: Health and Wellbeing e-Networks for All [33].

Abstract

Medical calculators play an important role as a component of specific clinical decision support systems that synthesize measurable evidence and can introduce new medical guidelines and standards. Understanding the features of calculators is important for calculator adoption and clinical acceptance. This paper presents a novel classification system for medical calculators. Metadata on 766 medical calculators implemented online were collected, analyzed, and categorized by their input types, method of presenting results, and advisory nature of those results. Reference rate, publication year, and availability of references were collected. We found the majority of calculators are likely not automatable. 16% of medical calculators present advisory results to clinicians. 83% of medical calculators provide references. We show a 9 year lag from publication to implementation of calculators. New medical calculators should be developed with EHR integration and the advisory nature of results in mind so that calculators may become integral to clinical workflow.

2.1 Introduction

Electronic health records (EHR) are becoming highly prevalent in hospital systems [34]. Clinical decision support (CDS) within EHRs is also ubiquitous. Technologies such as the SMART platform [16], the HL7 FHIR data interface [17], and CDS Hooks [18] are helping drive the development of CDS that can be used in any EHR system. At the same time, studies have shown quality, workflow, and efficiency benefits for users of decision support systems [35,36]; however, these benefits are not universal for all CDS [5,7].

Some CDS systems have medical calculators as a major component; therefore, it is important to understand medical calculator attributes. Medical calculators embody evidence-based medicine and are typically based on scientific literature [10]. Some medical calculators are embedded into EHRs and can be considered ubiquitous such as the automatic BMI calculation. The proliferation of technologies, such as the internet and EHRs, have obvious implications for the accessibility of patient data and access to medical calculators. While the majority of medical calculators are simple and straightforward, there exist many online, web-based medical calculators that may be provisioned within an EHR.

Workflow integration and dissemination techniques are common themes in literature examining CDS. Previous broad studies on CDS have identified workflow, adoption, effectiveness, and dissemination of knowledge as top challenges [12,13]. Appropriate integration of CDS has been problematic, with alert fatigue being well studied [37,38]. Recent studies have investigated the potential for automating calculation of medical calculators, highlighting the opportunities and challenges of doing so [39,40].

The appropriate provisioning of CDS was characterized by the "five rights": making the right information available to the right person, in the right format, through the right channel, at the right time [41]. The automatic provisioning of CDS can have a positive impact on important healthcare issues, such as patient safety [42], racial and gender disparities [43], and process adherence [44]. In addition, prior studies show that factors such as automatic provisioning of CDS tools [36,45] can impact the adoption and success of CDS. Moreover, the Kawamoto study [46] identified several important relevant factors driving CDS adoption that are applicable to medical calculators: a) automatic provision of decision support as part of clinician workflow, b) provision of recommendation rather than just an assessment, and c) computer-based generation of decision support.

Classification of medical calculators is an important topic that impacts provisioning techniques. There is no widely accepted standard classification of CDS, and no comprehensive taxonomy for medical calculators. Osheroff et al., proposed a generic CDS taxonomy based on user interface [41], while Berlin et al. developed a framework for the classification of CDS (the CDSS Taxonomy framework) [47]. Calculator inputs and outputs have not been well studied. Dziadzko et al. [48] classified a subset of online calculators by their specialty, calculation methods, and goal, but did not further describe the output modes of a calculator. Aakre et al. [40] studied the specific availability of the inputs of 168 clinical calculators within the EHR and classified them as easily extractable, extractable with advanced techniques, or not extractable, but did not provide a taxonomy to describe different input types and the impact those types have on automatic calculation. Of the existing literature, the Berlin et al. framework provides the most broadly applicable framework for assessing a CDS like medical calculators. Their Reasoning Method, Recommendation Explicitness, and Explanation Availability attributes are particularly pertinent to calculators due to their simple nature.

The importance of workflow integration and automation on CDS adoption is clearly defined in literature; however, current research does not address the specific contributions that the structure of a medical calculator may have on the ability to automate and integrate these types of CDS into EHR workflow. These currently unknown attributes of calculators may have a direct impact on medical calculator adoption. We expand the current state of CDS classification by identifying attributes that are unique to medical calculators. Their potential for automatic calculation and delivery of advisory information to clinicians and calculator input and output modalities are important factors for clinical acceptance and workflow integration. We also examine literature references of calculators to determine availability and lag between publication and implementation of online calculators.

2.2 Methods

We performed an assessment of three currently available online services that provide access to medical calculators, consisting of two free services and one commercial service. These services are anonymously referred to as Service 1, Service 2, and Service 3, respectively. The two free services were the first two non-medical-specialty specific web-based services appearing in the top 10 "organic" search results using the term "medical calculator" through a Google search. The commercial service was selected due to its availability in the University of Missouri Health System (UMHS). In total, these three online medical calculator services contained 766 implemented medical calculator algorithms.

Input types were determined by performing HTML data scraping of the HTML input tag from Service 3. Each input was classified into a type by examining the HTML input type (radio, checkbox, number, or text), and whether the data was a discrete value, a logical computation of a discrete value, required interpretation or the opinion of a clinician, or were worded in such a way as to require data from a patient and be unlikely to be stored in the EHR. The resulting types were checked for completeness during classification of the entire set of calculators.

Calculator output types were determined by examining all calculators in the study. Each calculator page was opened and classified into one or more of the output type categories. Categories were added as new output types were encountered. The calculators' targeted user (physician or patient) was captured and their references were collected where available. The calculator type was also assessed by examining the input and output modalities and targeted user to arrive at a classification. Calculators that did not fall into an already encountered type were assigned to a new type.

2.3 Results

Using the CDSS Taxonomy framework, we accounted for Reasoning Method, Recommendation Explicitness, and Explanation Availability during our data collection. Data inputs, calculator outputs, and calculator references were documented for each calculator in the three services. Calculators were then categorized based on these factors.

2.3.1 Calculator Inputs

To provide a generalized guide for future calculator development, we examined the inputs necessary for medical calculators and generally classified them as follows:

1. Discrete Data Elements – these are atomic pieces of data stored in an EHR. For example, the rate of creatinine clearance.
2. Non-discrete Data Elements – inputs of a non-discrete nature can ask for medical opinions of providers, for example, the likelihood of a diagnosis.
3. Logical Computation on discrete data elements – a calculator that asks if a value is over or under a certain threshold, or within a specified range, requires logical

computation to determine an input value. For instance, in a point-based calculator, assigning points based on age ranges falls into this category.

4. Obscure Data Elements – Data elements unlikely to be contained as structured data within an EHR. For example, the NIH Stroke Score requires the patient to identify the current month and his or her own age.

2.3.2 Calculator Output

For demand-driven calculators, the way in which calculator results are delivered (Recommendation Explicitness [47]) were considered germane in our review as they are related to the advisory nature of the calculator output. Advisory calculators suggest a diagnosis or recommendation, and non-advisory are assessment only, providing a probability, score, or discrete information result. We identified five different types of results display, classified as either non-advisory (types 3, 4, and 5) or advisory (types 1 and 2), with Table 2.1 showing the distribution of these.

1. Diagnosis – Calculator presents a potential diagnosis, for example the Duke Criteria for Infective Endocarditis [49] provides a definite, probable, or rejected diagnosis for infective endocarditis
2. Advice/Recommendation – Calculator suggests or recommends a specific course of action, such as the HEMORR2HAGES Score for Major Bleeding Risk [50] which suggests initiating therapy based on calculator results.
3. Probability – Calculator provides a probability of patient having or developing a condition. The APACHE II Score [51] provides a probability of mortality
4. Classification – Calculator classifies patient in one or more categories. For example, the Apgar Score [52] classifies infants as normal or requiring intervention.

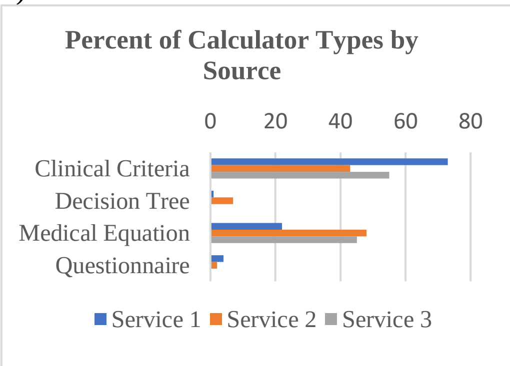
5. Discrete Information – Calculator provides a discrete data value for provider to use. The BMI calculator provides the well-known ratio of body weight to height.

Table 2.1 – Percentage breakdown of output types of calculators.
*Note that a calculator may present multiple output types.

	Service 1 (n=138)		Service 2 (n=498)		Service 3 (n=130)	
Output Types	Count	Percent of total	Count	Percent of total	Count	Percent of total
diagnosis	2	1.45	27	5.42	6	4.62
advice/recommendation	42	30.43	37	7.43	7	5.38
probability	23	16.67	41	8.23	4	3.08
classification	75	54.35	195	39.16	69	53.08
discrete data	33	23.91	249	50.00	56	43.08

Kawamoto [46] indicated that the success rate for decision support use is substantially higher for CDS that provision a recommendation versus an assessment. We found that just 16% (121/766) of calculators fall in the advisory category. With the majority of analyzed calculators not providing recommendations, there is a lower potential for significant adoption of medical calculators.

a)



b)

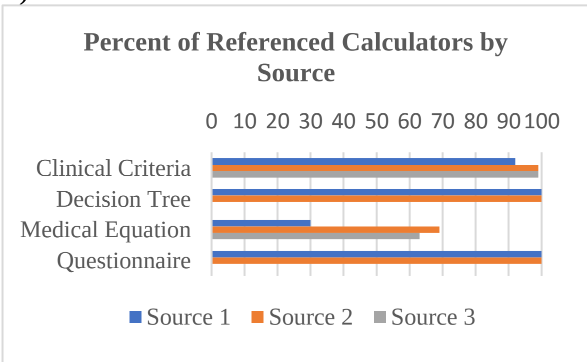


Figure 2.1 – Calculator Types and References by source.

A) shows that Clinical Criteria and Medical Equations are the most popular types of medical calculators. In b) we find that Medical Equations are far less referenced than the other types.

2.3.3 Calculator Categorization

Calculators in this study were analyzed and categorized into four major types:

1. Clinical Criteria – These are clinician facing calculators typically implemented as a scoring system. Answers to specific questions accrue points, with the total then looked up in a table to define the calculator output. These can require any combination of the four Input Types. For example, Total Cholesterol required by the ACC/AHA 2013 Cardiovascular Risk Assessment [53] accepts discrete data input. The Wells Score System for Deep Vein Thrombosis [54] asks for non-discrete data elements through questions such as “An alternative diagnosis is more likely than deep-vein thrombosis.” The Multiple Myeloma Diagnostic Criteria [55] has input with logical computation on discrete data elements (M Protein: IgG > 3.5 g/L). The Head CT Rule for Minor Head Injury [56] requests obscure data elements such as “Inability to bear weight right after the injury as well as in the emergency department”. Combinations of any of the input types may also be requested, as in the Metabolic Syndrome Criteria [57]: “Blood pressure >=130/>=85 or on blood pressure prescription”
2. Medical Equation – All inputs are Discrete Data Elements. The result of the calculator is found by computing a formula with the appropriate values. For example, the Cockcroft-Gault equation for estimating creatinine clearance is CreatClear = Sex * ((140 – Age) / (SerumCreat)) * (Weight / 72), where the value for Sex is 1 for male and 0.85 for female [58].
3. Questionnaire – Inputs can be any of the four Input Types and are designed to be answered either by a patient or in collaboration with a patient. A scoring system is

usually employed, similar to Clinical Criteria. An example is the CAGE Questionnaire [59], which contains input prompts such as “Have you ever felt you needed to cut down on your drinking?”

4. Decision Tree – Inputs presented to users are dependent on answers to prior questions. A scoring system is used similar to Clinical Criteria. The PECARN Pediatric Head Injury/Trauma Algorithm [60] is an example of a decision tree.

Figure 2.1(a) shows the distribution of calculators by type across the three analyzed calculator services. Clinical Criteria calculators make up the majority of catalogued calculators. Because they can require Input Types other than Discrete Data Elements, additional steps may be required by the provider to search the EHR or other sources for relevant data and could reduce the likelihood of utilization. Medical Equations make up the next largest category. These are the only type that rely solely on Discrete Data Elements. Given the availability of EHR data, they can be automatically computed without interaction from a clinician. Questionnaires and Decision Trees make up a collective minority of the catalogued calculators. Both types are designed to be highly interactive and thus do not lend themselves well to automated computation.

2.3.4 Calculator References

The rate at which references were made available, for which types, and the accessibility of those references, were collected during calculator analysis. The availability and access to references fulfills a portion of the CDSS Taxonomy framework’s “Explanation Availability of the Information Delivery axis” [47]. Clinicians can gain an understanding of the reasons behind a recommendation from the primary literature and is complimentary to the advisory content of medical calculators. The distribution of references by calculator type is presented in Figure 2.1(b). While the numbers of decision tree and questionnaire calculators were very small, we did note that Service 1 and Service 2 referenced 100 percent of these types. Clinical criteria calculators were referenced more than 90% of the time, with two services approaching full coverage. Medical equations were the least referenced type of calculator across the three services we analyzed.

Table 2.2 – Reference links provided by Service 2

Domain	Count
Internal Site Reference	47
Other URL	55
No URL Provided	65
www.ncbi.nlm.nih.gov	589

We found that each of the three services presented references in distinct ways. One service listed references in citation style, while the other two attempted to provide URL links and categorization of the references. A primary concern uncovered in our analysis was the accessibility of the references. We conducted a detailed analysis of the largest calculator service that provided URL links (Table 2.2). A deeper analysis of the NCBI links showed that they all led to PubMed, a site which makes freely available basic information on articles, such as publication year and abstract, but not the full text. Lack of access to full text references could be an important factor in the adoption of newly implemented medical calculators.

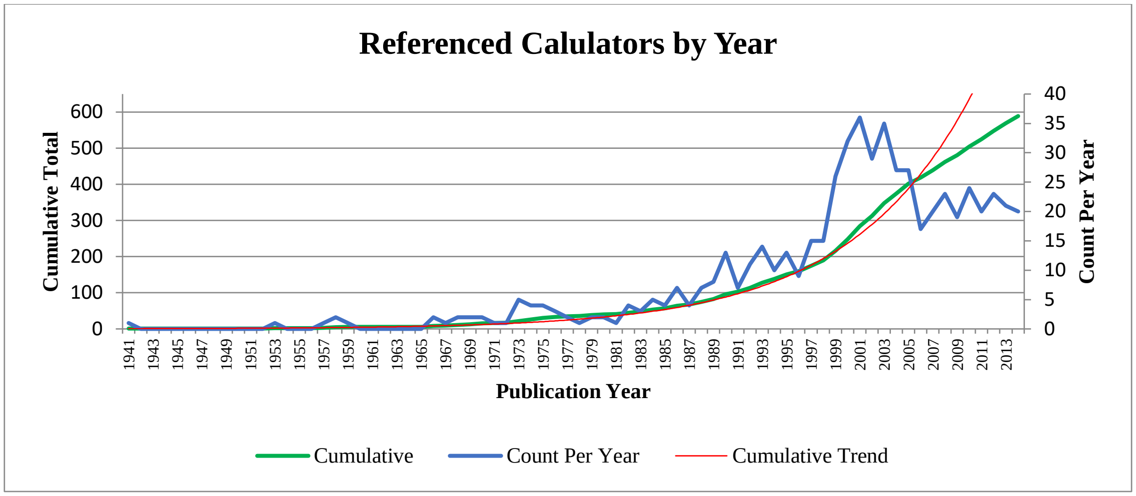


Figure 2.2 – Number of referenced calculators by year.

An analysis of the publication year of the NCBI references supported a trend towards older publications (Figure 2.2), with the median publication year being 2002. Growth of implemented calculators follows an exponential curve until 2006. In the same year, there is a change in the rate of medical calculator implementations. Because this analysis represents a single point in time snapshot of medical calculator implementations as of March 2015, and implementation dates of online medical calculators are not available, we can only hypothesize that the reason for the change in calculator implementation rate is a lag from publication to implementation of approximately 9 years. Studies of medical research publication to widespread practice implementation show a similar lag of 17 years [14] to 24 years [15].

2.4 Discussion

Our analysis shows that less than half of available medical calculators lend themselves to fully automatic calculation of results, with past research indicating that the adoption of CDS increases with automatic provisioning [46]. The ability of a calculator to have its results displayed automatically is rooted in the decisions made during the research that produced the calculator publication. While any calculator may be included in provider workflow at the "right time", only a minority of calculators could automatically provide the resulting answer without requiring a clinician to manually input data that may already be available in the EHR. Medical equations are the single type of calculator capable of providing the result without the interaction of the user due to the inputs requiring only discrete, structured data. Clinical criteria may be automated but may be challenging to develop due to the varying types of inputs that could be required. The other types of calculators (e.g. decision trees and questionnaires) are less suitable for automatic calculation due to their interactive nature. Thus, as new predictive models are developed, careful consideration should be given to the type of calculator that could be implemented. Medical equations and clinical criteria could be the preferred implementation if adoption and dissemination are desired for the model.

The advisory nature of current medical calculator outputs is also not consistent with prior studies that suggest recommendations lead to better adoption [46]. Only a small percentage of the calculators we studied (16%) provisioned results in an advisory fashion. Two of the most active forms of delivering medical calculator results included suggesting a diagnosis, and dispensing advice or recommendations for treatment. While we surmised that many factors play into the ability to provide advisory results, e.g. validation studies, liability, and confidence, it nevertheless is a factor related to adoption and should be considered in the development and publication of new predictive models.

Finally, 83% of implemented medical calculators in this study provided reference materials. The high rate of reference availability could prove a useful method of introducing new evidence-based medicine directly in the clinical workflow as embedded medical calculators; however, the inaccessibility of full text references may be problematic. It requires further study to determine whether or not reference availability would have an impact on perceptions of calculator credibility. The noted median year of publication of medical calculators was 2002, which highlights a potentially missed opportunity to leverage EHR deployed CDS as a means to introduce new evidence based medical literature.

2.5 Conclusion

This paper presents a taxonomy of medical calculators that can be used to inform future research in medical calculators and predictive algorithms. Researchers ultimately may be best positioned to impact the future of CDS adoption by becoming more cognizant of the types of data used to build these models, and the advisory nature of the results, and by being conversant in the fundamental structure of a medical calculator. These decisions may influence the speed at which new predictive models are implemented and delivered as automatic decision support within EHRs. EHR vendors and implementers should take note of the five rights of CDS, relevant usability and automation concerns, and disparities between different levels of clinical experience to design calculator workflows that are deployed automatically to end users. As CDS becomes more accepted as part of the delivery of medicine, evidenced by recent opinion [61] and the creation of "npj Digital Medicine" [62], insights into the issues surrounding integration of CDS into clinical workflow will help drive adoption of new technologies. We believe that future medical calculators will go beyond regression analysis and include more complex data, longitudinal data, and data from outside the EHR. Techniques such as deep learning, explainable AI, and big data technologies will make available more decision support that is based on discrete data in an EHR and can be automatically provisioned as medical calculators. Such disruptive and cutting-edge research will radically change medical practice in the coming decades, and contributions in this area must continue to push the comfort zones of the medical community. Building a solid understating in this area, as the collective research on medical calculators does, is necessary to prepare for such a future of digital medicine.

CHAPTER 3

3 Medical calculators: Prevalence, and barriers to use

The work in this chapter is published in the journal Computer Methods and Programs in Biomedicine [63].

Abstract

Background and Objectives

Medical calculators synthesize measurable evidence and help introduce new medical guidelines and standards. Some medical calculators can fulfill the role of CDS for Meaningful Use purposes. However, there are barriers for clinicians to use medical calculators in practice. Objectives of this study were to determine whether lack of EHR integration would be a barrier to use of medical calculators, and understand factors that may limit use and perceived usefulness of calculators

Methods

A survey about medical calculators as they relate to clinical efficiency, perceived usefulness, and barriers to effective use was conducted at a medium-sized academic medical center. 819 physicians were invited to participate in an online survey with a 13% response rate. Results were statistically analyzed to highlight factors related to use or non-use of medical calculators.

Results

We found a negative correlation between use of medical calculators and years of experience ($p<0.001$), with decreasing calculator use as experience goes up. Barriers to using medical calculators by non-users and users of medical calculators show that necessity

and integration are significantly different with $p<0.001$ and $p=0.037$, respectively. 46.7% of non-users reported necessity as a barrier compared to 7.7% of users. Integration was reported as a barrier for 43.6% of users, but only 13.3% of non-users. 61% of users indicated that calculators made them more efficient, and 70% reported that unavailability of normally used calculators make them less efficient. 60% of users indicated that they are somewhat or very likely to use newly published medical calculators.

Conclusion

The results highlight that medical calculators are important for care delivery by both users and non-users. For non-users, they are seen as having a potentially positive impact on patient care, but unnecessary as part of clinical practice. For medical calculator users, calculators are an important part of regular workflow for efficiency improvement. Clinicians with fewer years of experience show an eagerness to consume newly published calculators, making these kinds of CDS a potentially useful way to disseminate new medical evidence. The survey results suggest that when medical calculators can be automated and integrated into the EHR as part of everyday workflow then efficiency and adoption may increase.

3.1 Introduction

Electronic health records (EHR) have seen a large increase in hospital system penetration, with adoption in the United States increasing more than fivefold since 2008 [3], and in some European countries, adoption approaches 100% [34,64]. Guidance from the Centers for Medicare and Medicaid Services regard clinical guidelines, diagnostic support, and reference information as relevant forms of CDS [65], all of which can be provided by medical calculators [66]. Studies have shown quality, workflow, and efficiency benefits for users of decision support systems [35,36]. Recent innovations that facilitate CDS integration are being adopted by EHR systems, such as the SMART platform [16], the HL7 FHIR data interface [17], and CDS Hooks [18]. Third party solution vendors such as MedSocket [67] are also working to provide EHR solutions focused on integrating medical calculators for clinical decision support. These advancements are helping drive the development of universal CDS that can be plugged in to multiple EHR systems; however, clinicians have yet to fully benefit from CDS [5,7].

In this paper, we define medical calculators as *computer software which takes as input one or more pieces of patient supplied and/or clinically sourced data and returns a discrete answer through calculating an equation, traversing a decision tree/questionnaire, or executing an algorithm*. The proliferation of technologies, such as the internet and EHRs, have obvious implications on the accessibility of patient data and access to medical calculators. These medical calculators are simple and straightforward, and there exist many online, web-based medical calculators available that may be provisioned within an EHR [48,66]. Prior studies show that factors such as automatic provisioning of CDS tools [36,45] and provisioning recommendations rather than assessments [46] can impact the adoption and success of CDS. Recent studies have investigated the potential for automating calculation of medical calculators and highlighted the opportunities and challenges of doing so [39,40]. No study has investigated the impact that EHR integrated medical calculators may have on the likelihood of calculator use, nor is there a clear understanding of the barriers to use of medical calculators by clinicians.

Our objectives of this study were to 1) determine whether lack of integration and automatic provisioning of medical calculator results would be a barrier to use of medical calculators, and 2) understand factors that limit use and impact perceived usefulness of medical calculators.

3.2 Methods

3.2.1 Study Design

We employed a cross sectional study design leveraging an online, computer adaptive survey targeted at clinical users of an electronic medical records system. The survey was designed to collect basic demographic data on respondents and capture current attitudes and practices regarding the use of medical calculators, using categorical, binary, and open-ended questions. The survey instrument was electronic and adaptive in nature. REDCap [68] was used to develop and deploy the survey instrument. Participants who indicated they did not use medical calculators were presented with 11 questions (6 required responses), and those who indicated use of medical calculators were presented with 30 questions (25 required responses). Gender, role, and years of experience were gathered from all participants. Table 3.1 lists the question domains under survey, the number of questions per domain, and the nature of responses. Appendix A contains the survey questions by domain and response rate.

Table 3.1 – Overview of survey domains

Domain	Number of questions	Nature of Responses	Description
Awareness	4	5 Point Likert, Categorical	General awareness about medical calculators
Demographics	4	Categorical, Binary	Collect basic demographic information about participants.

Efficiency	3	Categorical	Assess the impact medical calculators have on work efficiency
EHR Integration	2	5 Point Likert	Questions related to integration of calculators in EHR
Frequency of Use	3	5 Point Likert, Categorical	Assess frequency and timing of use
Meaningful Use	2	5 Point Likert	Assess the use of calculators in a meaningful way, related to the US HITECH act
Nature of Use	5	Free Text, Binary, Categorical	Assess the way in which calculators are used
Perceived Usefulness	4	Free Text, Binary, Categorical	Understand the way in which calculator users feel they impact patient care
Usability	3	Free Text	Capture free text responses related to the usability of calculators

3.2.2 Setting

The survey was conducted at the University of Missouri Health System (UMHS), a mid-sized academic medical institution located in a predominantly rural area. UMHS operates more than 50 clinics and five inpatient facilities totaling 550 beds. UMHS has a system wide EHR provided by Cerner Corporation (PowerChart) that is used by staff to retrieve, document, and store patient medical records.

3.2.3 Participants

Physician, fellow, and resident email addresses, names and, when available, department affiliation were programmatically extracted from the online physician directory for the UMHS hospital and clinics, yielding 819 Physicians, Residents, and Fellows. Participation in the study was voluntary and no compensation was offered. The number of responses to the survey determined the study size.

3.2.4 Variables

The primary variables of interest included self-reported use/non-use of medical calculators, and the coded responses to the optional free text questions regarding barriers to use and features most liked about medical calculator products. Years of experience and department affiliation were considered potential effect modifiers for medical calculator use. Department affiliation was determined using the identified department from the search results used to collect survey participants.

Free text responses for barriers to medical calculator use were coded into distinct categories, and responses to the free text question asking for liked features of medical calculators were tallied by response/no-response. Verbatim responses for these variables were further used as supporting evidence for statistical analyses. Table 3.2 describes the coded categories for the free-text answers to the question for barriers to use.

Years of clinician experience was collected categorically by grouping into the following 10 ranges: 1, 2, 3, 4, 5, 6, 7-10, 11-20, and >20. Because of the teaching nature of the UMHS, it was surmised that there would be a stronger response from residents and fellows, so years of experience was presented more granularly for early career respondents. However, this was not supported by the responses, and so during the analysis phase the categories were collapsed into three groups representing early career (1-6 years), mid-career (7-20 years), and highly experienced (>20 years).

The types of medical calculator preferred by participants was asked. Participants could choose multiple options, and we offered three types to select: decision trees that walk you through a set of questions to arrive at a recommended action, equations based on discrete values from the patient's chart, and questionnaires that may ask about medical history of the patient [66].

Table 3.2 – Free text response categories for barriers to medical calculator use		
Question	Categories	Free Text Answer Types
Please describe any barriers that exist that prevent you from using medical calculators more. (Barriers)	Integration	Integration of clinical data with calculator
	Necessity	Perceived need
	None	Respondent explicitly stated no barriers
	Technical	Technical issues or limitations with computer/phone hardware
	Training	Indicated no knowledge of use or lack of training
	User Interface	Problems with the user interface
	Workflow	Clinical practice workflow interferes with or prevents use

3.2.5 Bias

We attempted to reduce selection bias by inviting all residents, fellows and physicians practicing medicine at UMHS to complete the survey. The invitation was made during a regular monthly newsletter sent to all participants by the Chief Medical Information Officer of UMHS, followed by emailed reminders after two and four weeks.

3.2.6 Statistical Methods

Free-text responses for the question asking about barriers to calculator use were categorized by one author with a separation of at least 4 months between two coding passes. Cohen's Kappa [69] was computed for intra-rater reliability. Discrepancies were resolved by a third party. Categories were determined by analyzing the responses to capture the main content of the response.

Chi-squared tests for independence were performed for barriers to use and liked features versus calculator use, years of experience and role to determine potential interaction. Two-tailed z-tests for differences between two proportions were used to determine the statistical significance of any differences in identified barriers between calculator users and non-users.

The Chi-squared statistic was used to test the correlation of calculator use to the individual variables of experience level, gender and role. The Chi-square test for independence was also performed on the department variable against the population to determine its role as a possible confounder. Chi-square was used to determine the independence of mode of calculator access to the report of EHR integration as a barrier. A logistic regression model was fitted for prediction of calculator use by years of experience classification to determine probabilities of calculator use by experience level.

3.3 Results

3.3.1 Participants

Of the 819 subjects invited to participate, 122 respondents clicked the survey link. 14 respondents did not complete the survey and were removed from further analysis, leaving 108 completed responses, a response rate of 13.2%. 6.8% (22/323) of residents responded, and 17.2% (86/501) non-resident physicians (encompassing attending physicians, fellows, and others) responded.

3.3.2 Descriptive data

Table 3.3 – Survey Demographics (n=108)

Calculator Use	Yes	No	Total
Total	73.1% (79)	26.9% (29)	100% (108)
Role			
Attending	60.8% (48)	79.3% (23)	65.7% (71)
Resident	25.3% (20)	6.9% (2)	20.4% (22)
Fellow	5.1% (4)	3.4% (1)	4.6% (5)

Other	8.9% (7)	10.3% (3)	9.3% (10)
Gender			
Female	39.2% (31)	31.0% (9)	37.0% (40)
Male	60.8% (48)	69.0% (20)	63.0% (68)
Years of Experience			
1-6	43.0% (34)	10.3% (3)	34.3% (37)
7-20	35.4% (28)	27.6% (8)	33.3% (36)
>20	21.5% (17)	62.1% (18)	32.4% (35)
Department			
Child Health	5.1% (4)	6.9% (2)	5.6% (6)
Emergency Medicine	2.5% (2)	0.0% (0)	1.9% (2)
Family and Community Medicine	10.1% (8)	3.4% (1)	8.3% (9)
Medicine	21.5% (17)	10.3% (3)	18.5% (20)
Neurology	2.5% (2)	0.0% (0)	1.9% (2)
Orthopedics	0.0% (0)	6.9% (2)	1.9% (2)
Physical Medicine and Rehabilitation	1.3% (1)	3.4% (1)	1.9% (2)
Surgery	5.1% (4)	3.4% (1)	4.6% (5)
Women's Health	2.5% (2)	0.0% (0)	1.9% (2)
Not Identifiable	49.4% (39)	65.5% (19)	53.7% (58)

3.3.2.1 Demographics

79 of 108 respondents reported use of medical calculators (73%). Table 3.3 lists the survey demographics. Due to a system processing issue during initial survey deployment, some responses were not linked back to the participant identifier, and thus department affiliation was lost. Those responses that were attributable came from nine different clinical departments. A Chi-square test of independence was performed to examine the relation between survey responders and department. The relation between these variables was not significant, $X^2(13, N = 819) = 8.864, p=0.783$.

Experience levels varied from one year to more than 20 years. Responses were split evenly across three experience groups: 1-6 years (residents) (34%), 7-20 years (early to mid-career) (34%), and more than 20 years (advanced) (32%).

3.3.3 Outcome data

79 survey respondents reported the use of medical calculators. 95% of these clinicians felt that using calculators positively affected patient outcomes, with 68% of those clinicians believing that the best outcomes are achieved by using calculators before or while they are seeing a patient. The most common access methods for calculators was through a smartphone app (56%) and websites (52%), followed by an integrated calculators component in the EHR (18%) and a manual chart/nomogram (13%). The most common types of calculators preferred was medical equations (86%), followed by decision trees (25%) and questionnaires (19%). 61% of users indicated that their use made them more efficient, and 70% reported that unavailability of normally used calculators would make them less efficient. 57% of calculator users report documenting calculator results in the EHR. 67% of users also reported using calculator results in a care plan. 60% of users indicated they are somewhat likely or very likely to use newly published medical calculators.

29 respondents reported they did not use medical calculators. Of the reported non-users, 79% included clinicians with more than 10 years of experience. 83% of these respondents reported that using medical calculators could positively affect patient care, even though they choose not to use them. The top reason selected in the survey for not using medical calculators was “They are unnecessary for patient care”, at 41% of respondents. 28% cited unawareness of them, and 28% chose “too hard/time

consuming/complicated". Cost was available as a reason in the survey but not selected as a factor by any respondent. 62% of non-users indicated they would be somewhat likely or very likely to use medical calculators if they were integrated into the EHR.

Respondents were asked to identify barriers to use in a free form text box which were then categorized (Table 3.4) using the methods described in sections *2.4* and *2.6*. The Cohen's Kappa for intra-rater reliability for coding the barriers question was 0.934, indicating almost perfect agreement [70]. 51% of all respondents did not write any input for this question. For those that did, integration with the EHR topped the list with 18% of respondents reporting it as a barrier. Workflow issues were next, with 10% of respondents indicating that as a barrier to use.

Table 3.4 – Response rate for free-text variables of interest

Variable	Categories	
Barriers	Integration	18% (19)
	Necessity	7% (8)
	None	6% (7)
	Technical	1% (1)
	Training	3% (3)
	User Interface	4% (4)
	Workflow	10% (11)
	Not answered	51% (55)
Features Most Liked About Calculators	Answered	39.8% (43)
	Not Answered	60.2% (65)

3.3.4 Main results

Because responses for barriers to calculator use and features most liked about calculators were not required, the Chi-square statistic was computed for the response profile against experience level (X^2 (2, N = 108) = 3.558, p=0.169), role (X^2(3, N = 108) = 5.836, p=0.120), and calculator use (X^2(1, N = 108) = 0.000, p=1.000). Similarly, the free text response rate for features liked was tested against experience level (X^2(2, N =

108) = 1.664, p=0.435), role (X^2(3, N = 108) = 3.552, p=0.314), and calculator use (X^2(1, N = 108) = 1.826, p=0.177). No significant relationship was found with these tests; therefore, we treat these response subsets as representative of the whole survey response set with regard to these demographic features.

When comparing the proportions of free-text categorized responses to barriers of use by users and non-users of medical calculators, necessity demonstrates significant difference between the two classes (Z=3.302, p<0.001), with 46.7% of non-users reporting necessity as a barrier to use compared to 7.7% of users reporting it as a barrier. The other significant difference was integration (Z=-2.085, p=0.037). Integration was reported as a barrier for 43.6% of users, but only 13.3% of non-users. The interaction between calculator user's preferred mode of access and reporting integration as a barrier was examined and found to have a significant relationship (X^2 (3, N = 17) = 19.841, p<0.001). Users that access calculators via a website or smartphone app were more likely to report integration as a barrier than those that reported accessing calculators via a manual chart or nomogram, or an EMR integrated calculators component.

Department information was available on 46% of responses. To reduce the possibility of self-selection forming potential bias in the analysis, a Chi-square test of independence was performed to examine the relation between departmental counts identified in survey responses and the departmental count of all clinicians invited to participate in the survey at UMHC. The relation between these variables was not significant, X^2(13, N = 819) = 8.864, p=0.783. We did not have department information available for all survey responses. We assume that the distribution of responses between the responders with and without department identified is the same, as the survey invitations were sent at the same time to all clinicians; however, we make no conclusions on the basis of department affiliation in this paper.

Years' experience	Probability of Calculator Use	95% Confidence Interval
1-6	0.919	(0.777, 0.974)
7-20	0.778	(0.615, 0.855)
>20	0.486	(0.327, 0.647)

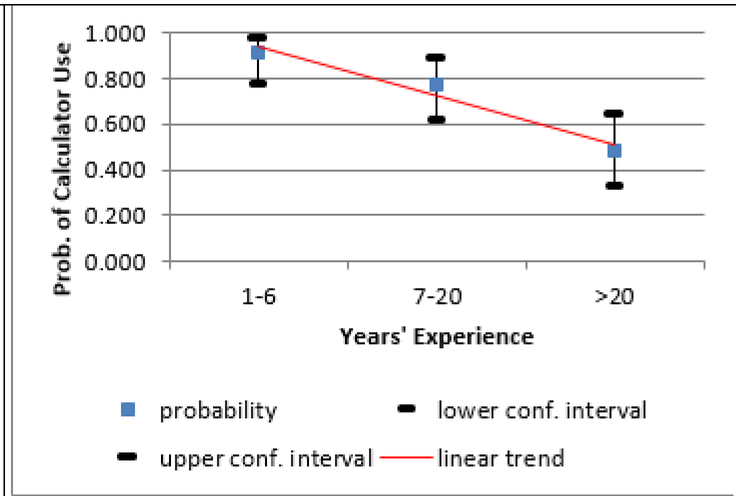


Figure 3.1 – Predicted probability of using medical calculators by years of experience.

The results of Chi-squared analysis of calculator use to experience, gender, and role was performed. The relation between calculator use and gender was not significant, $X^2(1, N = 108) = 0.311$, p=0.577, neither was the role of the physicians, $X^2(3, N = 108) = 4.814$, p=0.186. However, the relation between calculator use and years of experience was significant, $X^2(2, N = 108) = 17.774$, p<0.001. Fitting a logistic regression model with calculator use as the dependent variable and years of experience as the independent variable yielded a model showing decreased probability of use as experience rises (Figure 3.1).

3.4 Discussion and Conclusion

3.4.1 Key Results

Experienced clinicians made up a large proportion of non-users, and we found a statistical correlation and association between use of medical calculators and years of experience. We suspect earlier career providers access a much broader range of calculators due to lack of experience, while experienced providers may have developed habits which include the use of only specific or well-known calculators routinely. Free-text responses for identifying most liked features of calculators from early career (1-6 years' experience) show some support for this, with one respondent saying, "Makes patient encounters much faster and makes me feel more confident about my decisions" [sic]. Another early career respondent also noted "user friendly, give result of calculation, how to interpret results and citations of literature supporting their use" [sic]. One late career respondent (> 20 years of experience) noted doubts about the credibility of the available calculators and manual loading of data when addressing barriers to use: "Availability; knowledge about their credibility; need to load data myself" [sic].

The identified barriers to use may underlie the inconsistent views that use of calculators during a patient visit is the most beneficial, but with actual use occurring after the patient has left. This is further supported by 62% of calculator non-users reporting that they would use medical calculators if they were integrated into the EHR. Both free form and directed survey questions support that for at least some clinicians who report not using medical calculators, workflow and usability concerns may be the primary factor discouraging their use.

3.4.2 Limitations and Generalizability

While it is expected that survey results may be generalizable to other institutions, there are factors that may influence survey results such as the scale and recency of EHR implementation, EHR vendor, and general attitude towards the EHR. The response rate was 13.2%, with low representation by resident physicians, who may be the primary beneficiaries for delivering new evidence-based medicine via decision support tools.

Department affiliation was not available for 54% of respondents, potentially weighting the responses in favor of one specialty over another.

3.4.3 Interpretation

Prior research supports that the adoption of CDS increases with automatic provisioning [46], whereas previous analysis of online medical calculators [39] supports only a small percentage of medical calculator implementations are able to be automated. Our survey results support the view that lack of automation is a barrier to use, with 92% of calculator users indicating they would use an EHR integrated medical calculator feature, and 44% citing lack of integration as a barrier to use. Users that are accessing calculators through digital means such as a website or phone app identify lack of integration as a barrier significantly more than those using paper or already using an EHR integrated calculators component.

This survey highlights that medical calculators are seen as important for care delivery by both users and non-users. For medical calculator users, calculators are an important part of regular workflow, providing efficiency in daily use for care planning, supported by our findings in section *3.3*. For non-users, they are seen as having a potentially positive impact on patient care, but lack of perceived need restricts their use. 61% of calculator users reported that calculators made them more efficient, and 70% claim that their unavailability would make them less efficient. 62% of calculator non-users reported that they would use medical calculators if they were integrated into the EHR. These results suggest that when medical calculators can be automated and integrated into the EHR as part of everyday workflow, as BMI and LDL cholesterol commonly are, then efficiency and adoption may increase. Further, medical calculator users, primarily clinicians with fewer years of experience, show an eagerness to consume newly published calculators, making these kinds of CDS a potentially useful way to disseminate new medical evidence. For this to happen, integration should be considered an important factor in calculator development.

CHAPTER 4

4 Evaluation of an Electronic Health Record Embedded Pain Management Visual Decision Support Tool

The work in this chapter is submitted for a journal publication.

Abstract

Objectives

We examined patient-centric effects of a clinical decision support (CDS) system for pain management for inpatients with diverticulitis, pancreatitis, and abdominal pain.

Materials and Methods

167 days of activity log data from the Electronic Health Record (EHR) system were analyzed to determine whether the CDS was opened in a patient chart, resulting in 865 cases. Differences in mean pain score, pain medication regimen, discharge medications, and use of opioid antidotes were compared between patients who had the CDS opened in their chart and patients who did not.

Results

For the CDS use group, average pain scores (0-11 scale) were reduced by 0.7 (to below the level requiring intervention by the local hospital quality protocol) and mean number of pain-related medications prescribed per day were reduced by 27.5%. No correlation was found between the use of the CDS and prescription of different classes of pain medications at discharge, nor with the use of an opioid antidote for reversing overdose.

Discussion

Our study shows that a CDS for pain management can have significant effects on the patient-centric outcomes of pain experience and pain medication regimen. The CDS was naturally adopted, primarily by nurses, and employed for cases with longer lengths of stay, indicating a potential benefit for difficult cases.

Conclusion

There is a potential for improvement of pain and pain related medication management using an interactive CDS that consolidates pain-related information into a visual decision support tool. The retrospective methods developed in this study are applicable to future CDS studies.

4.1 Background and Significance

Effective management of pain has been the focus of recommendations by many organizations [23,24,71–73], yet it remains an elusive target [28]. When the American Recovery and Reinvestment Act of 2009 called for the implementation of EHRs in hospitals and doctor's offices [74], opportunities were created for retrospective analysis of clinical EHR data. Data collected by EHRs provide fertile ground for retrospective analyses and the development of clinical decision support systems (CDS) in the area of pain management [19]. Common approaches to CDS for pain management include patient interactive systems [75–77] and decision trees that guide providers through predetermined protocols [32]. Protocol-based CDS are effective at guiding management of problem conditions according to the standard, but there are clinical exceptions that require an override of CDS recommendations. This paper reports on a study of a CDS tool for patients with acute abdominal pain in an academic health care center. The academic health care center where the research was conducted had protocols in place to address acute pain for inpatients when the pain reached a level of four on the Numeric Rating Scale of 0-10 (NRS-11).

Literature about the use of CDS for the management of abdominal pain is sparse. Eleven studies focused on abdominal pain from the perspective of diagnosis [20,78–83], screening [84–87], risk assessment tools [88], or mobile applications and alerting [89]. In the review by Pombo et al. [19], only 19% of the studies focused on treatment, and 32% were related to abdominal pain. Only one abdominal-pain-related study reviewed for this paper published results related to patient outcomes [83] while the others focused on CDS accuracy. These systems are based on measurable and documented clinical events with automated scoring or classification, and as a rule they leave out the clinician as an influencer on pain outcomes [90]. Pain-relevant clinical and non-clinical factors have been documented in the literature [91–98]. Additionally, care providers have an experience-based sense of which factors are important to consider in the treatment of acute pain [99]. EHR design does not often lend itself well to rapid assessment of these factors in a comprehensive manner. Potentially relevant pain-related factors are scattered throughout the EHR, which is a barrier to the rapid and comprehensive identification of pain [100]. Cognitive load [101] is high for providers wishing to simultaneously consider all potentially relevant pain related factors for a single patient.

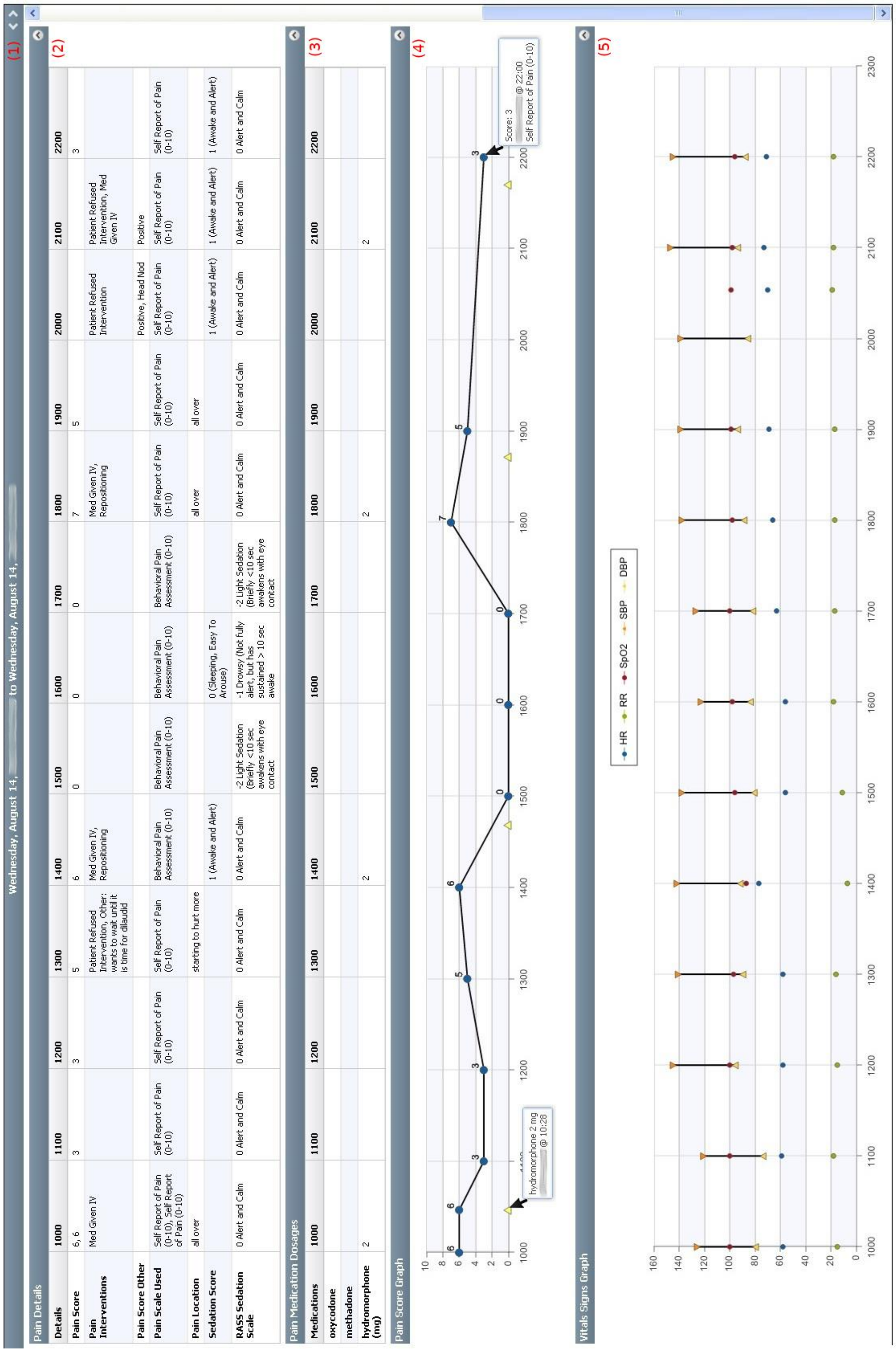


Figure 4.1 – The Pain Management CDS
(1) Date/time selection, (2) Pain Details (numeric and textual), (3) Pain Medication Dosages, (4) Pain Score Graph (with med administration markers), (5) Vital Signs Chart

4.2 Objectives

This paper reports on a retrospective study of a CDS for pain management by testing the effect of the system on patient outcomes related to pain management. We examine the significant differences a pain management CDS can make on patient-centric outcomes, including self-reported pain [102], stability of pain medication regimen [72], the prescription of medications at discharge [26], and the use of opioid antidotes during the inpatient stay [71,103].

4.3 Methods

4.3.1 Study Design

A Pain Management CDS was made available to all clinicians at a mid-size academic medical center on September 9, 2015 and was visible as a selection on the left-hand side of the EHR from any screen. The availability of the CDS tool was announced to all practicing clinicians at the time of release, and training was offered through the medical center's clinical education department. Use the CDS was not required, and training was optional. The analysis was a retrospective cross-sectional design, with patient visits assigned to a group based on natural clinician use of the CDS. The project was reviewed and approved by the Institutional Review Board of the medical center, project #2007767 HS.

4.3.2 Development and Pilot of The University of Missouri Pain Management CDS

The Pain Management CDS was developed using web-based technologies, embedded in the EHR, and released as a pilot in September 2015. The tool is visual in nature (Figure 4.1) and was developed in conjunction with clinicians to display the most relevant pain-related clinical data in a 12-hour timeline view.

The sections are as follows:

1) Date/time selection: The user can move forwards and backwards through time or select a specific date/time.
2) Pain Details: Details of pain related clinical documentation (numeric and text), including pain scores and related scales, and non-pharmacologic pain interventions.
3) Pain Medication Dosages: Medication administrations with dosage for all active pain related medication orders (Table 4.1).
4) Pain Score Chart: Chart showing pain score over time, with markers for medication administrations. Hovering with the mouse displays additional content.
5) Vital Signs Chart: Chart showing heart and respiratory rate, blood pressure, and SpO2.

This tool was designed to provide fast access to a set of information that was considered clinically relevant to pain management. Clinician input was collected through expert interviews on the subject matter with a group of physicians from the internal medicine department. The interviews were used to collaboratively design the layout of the CDS with a team of developers and collect the list of medications (Table 4.1), relevant vital signs and other pain related clinical events that appear within the CDS. Test group clinicians were provided clinical access to development versions of the CDS in a testing environment containing actual patient data. These clinicians made recommendations and the developers promoted changes for further review.

Table 4.1 – List of medications included in the Pain Management CDS

Medication Category	**Medication List**
Antidotes	flumazenil, naloxone, naltrexone
Anxiolytics	chloral hydrate, hydrOXYzine
Benzodiazepines	ALPRAZolam, diazepam, LORazepam, midazolam, temazepam

Combinations	acetaminophen-codeine, acetaminophen-HYDROcodone, acetaminophen-oxyCODONE
General Anesthetics	ketamine, propofol
Narcotics	codeine, fentaNYL, HYDROmorphone, meperidine, methadone, morphine, nalbuphine, oxyCODONE, remifentanil, SUFentanil, traMADol
Non-narcotics	acetaminophen, APAP/butalbital/caffeine, celecoxib, ibuprofen, indomethacin, ketorolac, meloxicam, nabumetone, naproxen, piroxicam, sulindac
Opioid Receptor Antagonists	methylnaltrexone

Patient data were collected on the Pain Management CDS pilot from September 9, 2015 to January 31, 2016 for patients with certain diagnoses.

Inclusion criteria were as follows:

1) Patients with a diagnosis of acute “abdominal pain”, “diverticulitis”, or “pancreatitis”, admitted to an inpatient unit between September 9, 2016 and January 31, 2016. Patients with both “abdominal pain” and one of “diverticulitis” or “pancreatitis” were classified with the more specific diagnosis. There was a single patient with “diverticulitis” and “pancreatitis” who was classified as “diverticulitis”. Because the study period fell over the transition from ICD-9 to ICD-10, both codes were used to select patient diagnoses:
    a. ICD-9
        i. Abdominal pain: 789.00, 789.01, 789.02, 789.03, 789.04, 789.05, 789.06, 789.07, 787.09
        ii. Diverticulitis: 562.01, 562.03, 562.11, 562.13
        iii. Pancreatitis: 57.70, 57.71
    b. ICD-10

i. Abdominal pain: R10.0, R10.1, R10.11, R10.12, R10.13, R10.3, R10.31, R10.32, R10.33, R10.84, R10.9

ii. Diverticulitis: K57.0, K57.01, K57.12, K57.13, K57.2, K57.21, K57.32, K57.33, K57.40, K57.41, K57.52, K57.53, K57.8, K57.81, K57.92, K57.93

iii. Pancreatitis: K86.0, K86.1, K86.9

2) Patient's self-reported pain scores using the NRS-11 were collected and filtered for unusable data. Scores were removed that fell outside of the range 0-10 or contained non-numeric characters.

Exclusion criteria:

1) Patients younger than 18 and older than 89 were excluded from the study. This was a study using de-identified data. Patients 90 and older are not considered de-identified when age is included in the data set. Younger patients are more likely to have their pain measured using a different scale such as NIPS, CRIES, or FLACC, therefore the study was limited to adults of 18 years or older.

2) Encounters where there were no pain scores above three were excluded. The hospital's pain management protocol at the time of the study did not indicate proactive pain management intervention for pain scores below four.

4.3.3 EHR Activity log processing

Patient visits with an appropriate diagnosis were classified into a "CDS" group and "no-CDS" group based on whether the Pain Management CDS was opened in a patient's chart during a hospital encounter in the study period. This determination was made by examining detailed EHR trace log data showing every action that clinicians took within the EHR for a given patient session.

EHR trace log data accumulated at a rate of approximately 1 GB per day. Not every record in the log contained a link to a patient or an encounter. The data were preprocessed using Python programs to group individual log records into EHR sessions and then associated with a patient and encounter. The programs used the process ID and operating system username written with each log record, along with a log record indicating the startup of the EHR program. The patient and encounter links were then propagated to all records in the group. In cases where EHR sessions had no patient or encounter links recorded, those sessions were unattributable and discarded. In other cases, EHR sessions contained links to more than one patient or encounter, indicating that the EHR user switched between patient records. Those EHR sessions were discarded as it was not possible to determine which patient or encounter the Pain Management CDS use may have been intended for.

Analysis of the log data found eight specifically labeled records in the log file written for each complete rendering of the Pain Management CDS screen. Because the EHR allows users to select a different EHR function before an EHR screen is completely rendered, only instances where all eight records were written were considered as a CDS use. Only instances where at least 2 and less than 300 seconds passed from the final CDS render to the next EHR function selected were considered as use of the CDS. Based on the content of the CDS we felt that less than 2 seconds was not enough time (based on 110 words per minute reading speed [104]) to absorb significant material presented and therefore not considered to be a qualified use of the CDS. Cases where the CDS was opened for more than 5 minutes (a conservative estimate based on similar data dashboard research [35]) were discounted as use because it was not possible to determine if the clinician was actively engaged in using the EHR versus leaving the chart open while performing other tasks. Because the primary interest of this study was whether the use of the CDS impacted pain scores, only those patient encounters that included pain score measurements both before and after the first use of the CDS were classified in the CDS use group.

4.3.4 Patient Data

From the EHR activity log, we collected the clinical role of the EHR user, how many seconds were spent with the pain management CDS open on the EHR screen, and a link to the patient and encounter for the EHR session. Demographic data were collected on the patient population, including diagnosis, gender, and age. Summary data were calculated for each patient visit as follows:

1) The mean pain score per patient per visit
2) The number of pain scores recorded per patient per visit
3) The length of hospital stay per visit
4) The number of hours before the first use of the Pain Management CDS per patient per visit
5) The mean number of seconds the clinician spent on the Pain Management CDS before selecting a different EHR function per patient per visit; uses below 2 seconds and above 300 seconds were removed from consideration
6) The number of medication orders for pain related medications (Table 4.1), normalized by length of stay in days, per patient per visit.

The incidences of opioid antidote use for each class (CDS and No-CDS) were summarized from the orders log for each patient visit. The distribution of clinician role was also collected for all uses of the CDS.

4.3.5 Statistical Methods

We performed a Chi-square test for equality of proportions on the distribution of diagnoses across the CDS and No-CDS groups to test whether the group's compositions were similar with respect to diagnoses.

We used t-tests to test differences in means for pain scores between the CDS and No-CDS groups for the first 8 hours of each patient visit as a baseline and for the entire encounter. The t-test was also used to compare mean pain scores of the CDS group before and after the first use of the CDS, the number of medication changes per day, the hours from arrival to first dose of an opioid antidote, and the number of opioid antidotes. For all of the t-tests performed, Levene's test was used to confirm assumptions of equal variances when necessary. When variances were not equal at a significance level of 0.05, Welch's t-test was used, otherwise Student's t-test was used, as noted in the results.

Median length of stay was compared between the CDS and No-CDS groups using Mood's median test, as Levene's test confirmed unequal variances at a significance level of 0.05.

Differences in discharge medication proportions of 4 categories of pain related medications was tested using the chi-squared test. The difference in proportions of opioid antidote use between the CDS and No-CDS groups were tested using the z-test for differences of proportions.

4.4 Results

There were 24,117 pain scores related to patients in the inclusion criteria. The Pain Management CDS was utilized on 21.4% of patient encounters in this study. Because the sample size of each group differs significantly (Table 4.2), we performed a Chi-square test for equality of the proportions of diagnoses across the CDS and No-CDS groups. The results showed no significant difference in proportions ($X^2=115$, $p=0.944$); therefore, we conclude that although there are roughly 3 times as many patient encounters in the no-CDS group, the distribution of diagnoses are similar. The primary users of the Pain Management CDS were nursing staff, accounting for 83.8% of all CDS views.

Table 4.2 – Patient demographics

		CDS		No-CDS	
		Frequency	**Percent**	**Frequency**	**Percent**
Diagnosis					
	Abdominal Pain	157	84.9	578	85.0
	Diverticulitis	10	5.4	33	4.9
	Pancreatitis	18	9.7	69	10.1
Gender					
	Female	95	51.4	377	55.4
	Male	90	48.6	303	44.6
Age					
	18-24	8	4.3	38	5.6
	25-34	17	9.2	83	12.2
	35-44	16	8.6	98	14.4
	45-54	27	14.6	137	20.1
	55-64	51	27.6	139	20.4
	65-89	66	35.7	185	27.2
Total		185		680	
Position					
	Nursing	310	83.8		
	Physician	60	16.2		
Total		358			

Table 4.3 – Summary characterization of patient visits and use of the Pain Management CDS

	CDS		**No-CDS**		**Difference**		
	Mean / Median	Std Dev	Mean / Median	Std Dev	Mean / Median	p-value	95% CI
Mean Pain Score per Encounter Baseline [c]	5.02	3.22	5.52	2.84	0.50	0.080	(-1.047, 0.059)
Mean Pain Score per Encounter [b]	3.82	2.24	4.50	2.33	0.68	<0.001	(-1.054,-0.302)
Length of Stay (hrs) [a,d]	195.01	274.98	80.85	109.46	114.16	<0.001	-
Medication Changes per Day [c]	3.22	2.41	4.44	3.64	1.22	<0.001	(-1.663,-0.772)
Mean Hours before CDS Use [b]	97.39	125.24	-	-	-	-	-
Mean Seconds of Use [b]	31.07	40.65	-	-	-	-	-
	Pre CDS Use		**Post CDS Use**		**Difference**		
	Mean	Std Dev	Mean	Std Dev	Mean	p-value	95% CI
Mean Pain Score per Encounter [b]	4.32	2.66	3.51	2.49	0.81	<0.001	(0.453, 1.166)

[a] Median was computed because the data were positively skewed
[b] Student's t test
[c] Welch's t test used due to unequal variances
[d] Mood's median test used due to unequal variances

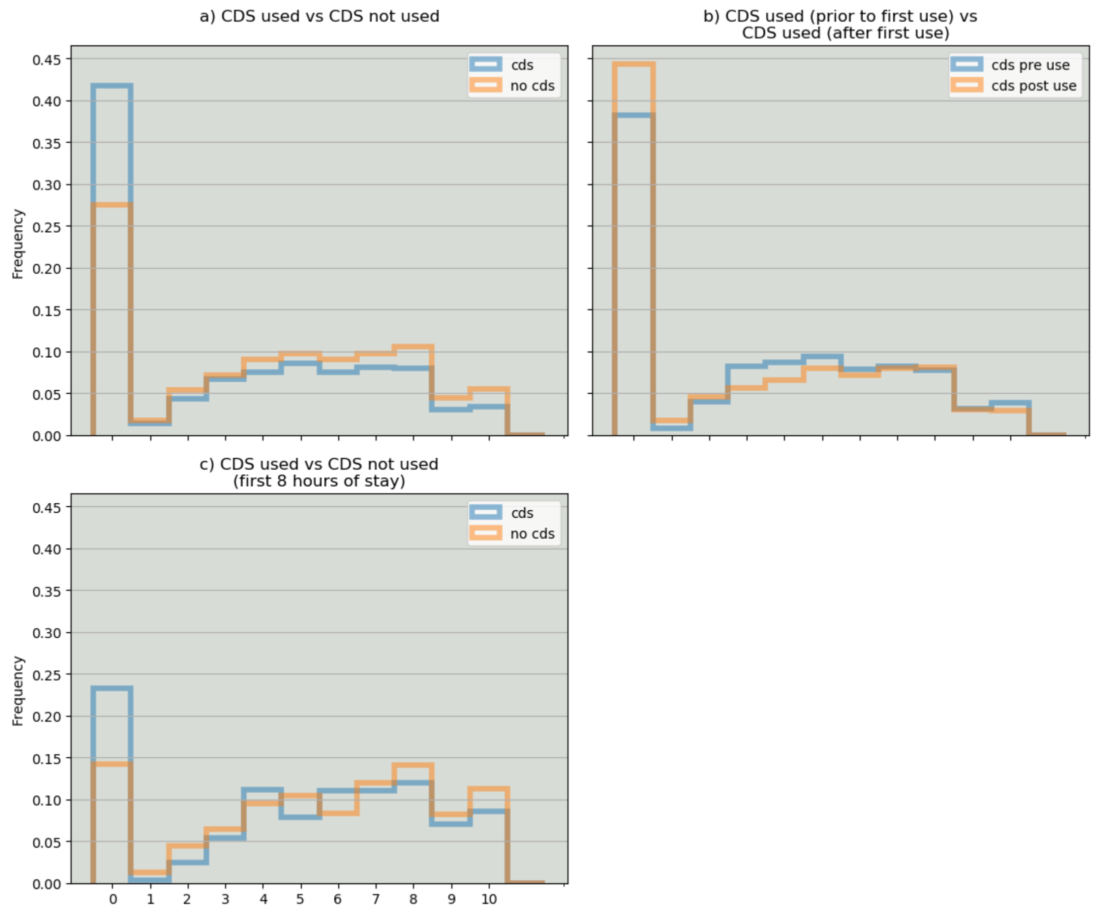


Figure 4.2 – (a) Pain score distribution between CDS and no CDS groups. (b) Distribution of pain scores before and after use of CDS (c) distribution of pain scores for first 8 hours of the inpatient visit

Table 4.3 describes the summary measures calculated for each group. A baseline comparison of pain was done for pain scores in each group for the first eight hours of the inpatient visit. The difference in the mean pain scores between the CDS group and the No-CDS group of -0.5 was not statistically significant (D=0.5, p=0.080, CI=(-1.047, 0.059)) (Figure 4.2c).

There was a significant difference in the mean pain scores between the CDS group and the No-CDS group (D=0.68, p<0.001, CI=(-1.054, -0.302)). Patients in the CDS group experienced lower pain scores by 0.68 on average than those in the No-CDS group (Figure

4.2a). To further examine this association, the difference in pain scores for the CDS group was examined by taking the mean pain score prior to the first use of the CDS and comparing it to the mean pain score after the first CDS use. The Student's t-test for paired samples was used, and a significant difference was found between the pre-CDS and post-CDS subgroups ($D=0.81$, $p<0.001$, $CI=(0.453, 1.166)$) (Figure 4.2b). Patients experienced an average drop in mean pain scores of 0.81 after the first use of the CDS. The median length of stay was 114 hours longer for those patient encounters where the CDS was used.

Next, the effect of the CDS on medication changes was examined. The number of pain related medication changes was normalized by dividing the total number of changes by the length of stay in days, giving the number of pain medication orders per day. We tested the hypothesis that medication changes per day were not equal between the two groups using an independent samples Welch's t-test. There was a significant difference in the count between the CDS and no-CDS groups ($D=1.22$, $p<0.001$, $CI=(-1.663, -0.772)$). The mean difference in medication changes per day was 1.22 fewer in the CDS group versus the No-CDS group.

Discharge medications were categorized on the subset of patients that had pain related medications prescribed upon discharge to determine if CDS use had an impact on these. Medications from Table 4.1 in the following four classes were used: benzodiazepines, combination narcotic analgesics, narcotics, and non-narcotic analgesics. We calculated the frequencies of each type of medication ordered compared to the total number of patient encounters in each class of CDS and no-CDS (Figure 4.3). There was no statistically significant difference in the proportions of medication classes prescribed at discharge ($p=0.212$).

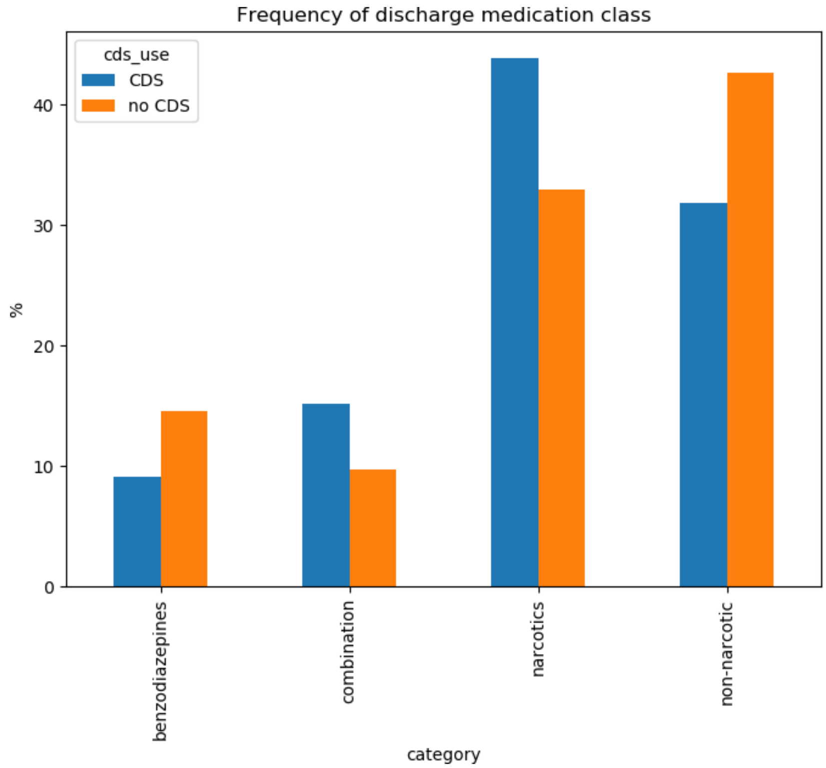


Figure 4.3 – Frequency of medication classes at discharge for CDS and no CDS use groups

Finally, the incidences of opioid antidote administrations were compared across the two groups to determine if the CDS helped to prevent opioid overdosing. Frequencies of encounters by CDS group where an antidote was used at least once or not used are shown in Figure 4. A z-test of the difference of the two proportions found no significant difference (D=0.0001, p=0.996, CI=(−0.047, 0.047)). There was also no significant difference in the time a patient was in the hospital before receiving their first dose of an opioid antidote, nor in the number of doses (Table 4). The percentage of CDS group patients who received an opioid antidote dose prior to the first use of the CDS was 82.4% (14/17).

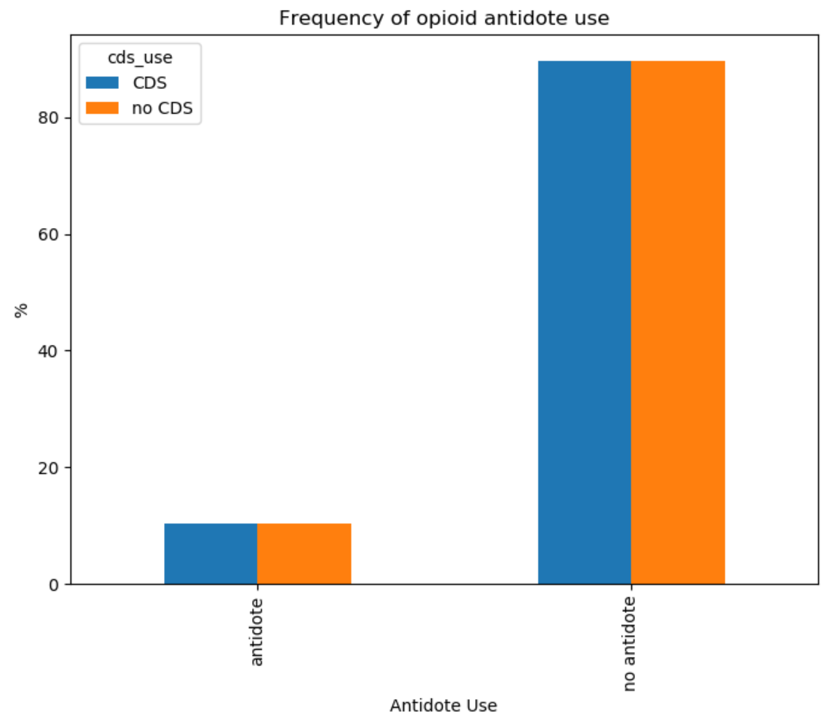


Figure 4.4 – Frequency of opioid antidote use for CDS and no CDS use groups

Table 4.4 – Student's t-test of time from arrival to first opioid antidote dose, and number of doses

	CDS		**No-CDS**		**Difference**		
	Mean	Std Dev	Mean	Std Dev	Mean	p-value	95% CI
Hours from arrival to first dose	64.44	86.25	41.85	83.77	22.59	0.279	(-18.62, 63.79)
Number of Doses	1.91	0.97	2.03	1.40	0.12	0.709	(-0.762, 0.520)

4.5 Discussion

The Pain Management CDS tool was used for 21% of patient visits in this study, and when it was used, on average clinicians waited until halfway through a patient's stay before using the tool. The median length of stay was 115 hours longer on average for those patient encounters where the CDS was used. This may reflect that clinicians had more opportunity to discover and use the CDS, and when taken in conjunction with the mean of 97 hours post patient admission before first use of the CDS, may reflect that the CDS was used on patients experiencing difficult to control pain, complicated, or longer stays [29].

The primary users were nursing staff, with nearly 84% of all views by nurses. In contrast, the systematic review by Pombo et al. identified 60% of all abdominal pain management CDS use targeted physicians only. Clearly nurses were in a better position to monitor patient's pain in this study than physicians were. The amount of time spent in the EHR with the CDS open varied greatly, with an average time of 31 seconds. There is statistical evidence to suggest an association between the use of this tool and a reduction in the mean pain score for a patient's inpatient stay. It was observed that pain scores averaged over a patient stay were reduced by 0.68 on the 0-10 pain scale. CDS use was also followed by a drop in mean pain scores of 0.81.

While the reduction in pain score in these tests is statistically significant, the *clinical* and *operational* significance of that reduction are also important. Because pain scores are inherently subjective in nature, there are no objective tests for pain reduction that can be relied upon to firmly answer whether a reduction of 0.68 for the CDS vs No-CDS group and 0.81 for the pre-CDS versus post-CDS use group are clinically significant. Prior studies found varying amounts of clinically relevant pain reduction [102,105–108], with NRS-11 based studies suggesting 1.39 to 2 is minimally clinically significant. Although our evidence does find an association with lower average pain scores, it would be difficult to conclude in a retrospective study that the use of the CDS made a positive impact on the subjective experience of a patient's pain. Operationally, at the hospital where the study took place, the pain management protocol for analgesic intervention set an action threshold of four for pain scores at the time the CDS was in pilot. Any patient with a pain score of four or above required intervention to attempt reduction of the pain score. This study found a reduction in average pain score below the actionable threshold when comparing CDS use versus no use, and pre CDS versus post CDS use. This suggests that the CDS tool may have helped to manage patient pain below the threshold.

The most significant findings of this study revolve around the associations between CDS use and medication-prescribing behavior. The data clearly show no difference between the two groups when it comes to reduction in prescribing pain-related discharge medications. Published guidelines for treatment of pancreatitis [109] and diverticulitis [110] are mixed on analgesic class recommended for pain control. There is no recommendation for managing pain in acute diverticulitis, and pancreatitis guidelines suggest using narcotics. There is, however, a significant reduction in the number of pain-related medication orders over the course of a hospital encounter. The data show a reduction by over one order per day (a 27.5% reduction) when the Pain Management CDS was used, which could indicate more effective pain management. Opioid antidote administrations were not correlated with the use or non-use of the CDS. Opioid antidotes are a class of life-saving rescue drugs used to treat respiratory depression in patients that may have been over-sedated by hospital administered narcotics, or through medication or drugs received prior to arrival. Literature suggests varying rates of rescue by these drugs of 0.038% to 5.2% of patients [71,103], with some of the variability attributed to mode of delivery. The rates are also higher for elderly patients. The rates observed in this study are higher than the expected rates reported in literature, which may indicate the population under study is more likely to be treated with narcotics than the inpatient population as a whole. Additionally, the highest-frequency age groups for both CDS and No-CDS patients is the 65-89 category, suggesting a higher vulnerability to respiratory depression. Closer inspection of the relative time of first opioid antidote administration to the first CDS view shows that of the 17 patients given an opioid antidote, 14 were administered prior to the first view of the Pain Management CDS and may be the result of reversing overdose encountered prior to admission.

4.6 Limitations

This study is limited by the number of patient visits observed and by the retrospective nature of the study. While it is not possible to know the reasons for use of the CDS, it is encouraging that the CDS was used without a mandate requiring it, suggesting that an organically discovered EHR feature may be proven useful. The nature of the study design did not allow for collection of subjective data from users of the CDS. It would be an important point for future work to understand the different ways nurses may have used the CDS versus physicians. The main diagnoses chosen for the retrospective study were based on the experience of abdominal pain, which were described by clinicians as difficult to control. Co-morbidities were not accounted for, although chronic abdominal pain was excluded from this study when identified. Patient-controlled analgesia administrations were not available from the medical record and therefore not included in this study. This study was performed at a single institution using a single EHR, and therefore its results may not be applicable to other institutions or other EHR systems.

4.7 Conclusion

Control of pain remains an important and elusive target. The results of this study of a Pain Management CDS indicate a potential for improvement of pain related medication management using an interactive CDS that consolidates pain related information into a visual decision support tool. There is also statistical evidence that use of the CDS is associated with an overall reduction in average pain scores, and that reduction may be operationally, if not clinically, significant. These findings are consistent with prior studies of pain related CDS which generally indicate mixed results. It is important to note that in this study, nurses accounted for a large proportion of CDS use, whereas in past studies access to pain management CDS was generally limited to physicians, which may be important in assessing content of future Pain Management CDS. Finally, this study helps to fill in the gap of patient outcome related effects of CDS focused on abdominal pain.

CHAPTER 5

Conclusions

5.1 Contribution to Informatics

In Chapter 2, we examine a subclass of clinical decision support by taking an in-depth look at medical calculators. Classification of medical calculators is an important topic that impacts provisioning techniques. While there are existing standards for CDS classification, such as by user interface [41] or specialty, calculation methods, and goal [48], we expanded the current state of CDS classification by cataloging the unique attributes of medical calculators. Our focus was on those features that were important for the practical considerations of implementation, integration, automation, and adoption. In Chapter 3, we turned our attention to the assessment of the prevalence of use of medical calculators as a CDS tool, and to the barriers to using medical calculators in practice. No study had investigated the impact that EHR-integrated medical calculators may have on the likelihood of calculator use, nor was there a clear understanding of the barriers to use of medical calculators by clinicians. In Chapter 4, we addressed the potential for an EHR-integrated CDS tool to impact the management of acute pain in an inpatient setting for specific types of abdominal pain. Opioid use for the management of acute pain is the standard of care for some acute abdominal pain, and we assessed the ability of this CDS tool to reduce reliance on opioids for pain management as an outpatient prescription. Current approaches for pain-related CDS encompass traditional predictive modeling and computerization of predetermined clinical protocols. In this work, we examined the effects of a different style of CDS that is visual in nature but leaves the decision-making in the hands of the clinician. We also expanded the understanding of how a pain management focused, EHR-integrated CDS could impact outcomes that are important for patients, such as pain control, as well as the socially impactful incidence of opioid use at home.

5.2 Features of Medical Calculators that Impact Adoption

In Chapter 2, through the examination of over 700 implemented medical calculators, we were able to derive a new taxonomy that specifically focuses on a subset of CDS. In this way we were able to highlight the features of medical calculators that can impact adoption.

By starting with a classification of input and output data for calculators, we built a foundation upon which the calculators themselves could be organized. Calculator inputs were found to fall into four categories: discrete, non-discrete, logical computation, and obscure. These input data types not only help categorize the calculators in which they are used, but also provide interesting and valuable insight into the process by which medical calculators are developed. Discrete data elements are atomic pieces of data that are readily stored in and retrieved from an EHR; however non-discrete and obscure data either require additional work to extract or are simply not available. Traditional medical research has been performed typically through prospective randomized controlled trials or other prospective methods which are considered to be superior to retrospective methods. Prospective methods have the advantage of tightly controlled confounders and processes but have the disadvantage of collecting data outside of what is typically considered normal clinical practice in many cases. Predictive models based on these data are then subject to an unavailability of data or require the collection of additional data on a case-by-case basis.

The ultimate trickle-down effect of this process is that only a minority of medical calculators can be automatically calculated with data that is easily extracted from an EHR.

A similar effect of the research process can be seen when looking at the output from medical calculators. In our research, we found five classes of output: Diagnosis, Advice/Recommendation, Probability Score, Classification, and Discrete Data. We classified these on an advisory continuum, with Diagnosis and Advice/Recommendation being the most advisory and the remaining being non-advisory. As we referenced in section 2.3.2, prior studies have confirmed a relationship between CDS adoption and the advisory nature of the CDS, with those CDS providing advice or recommendations having higher adoption rates than those that do not. We suggested a number of factors that could lead researchers to produce a predictive model that is not advisory in nature. Liability concerns may also impede the development and delivery of medical calculators that provide advisory results [111].

Another reason for the lack of advisory result calculators has to do with confidence and validation. Primary research for predictive modeling is usually focused on the proof of a hypothesis, such as whether some set of clinical factors are correlated or associated with a particular outcome. Once the hypothesis is proven, the focus moves to generating a publishable manuscript. These studies may have limitations, such as single-institution data or low enrollment, and so validation studies are a necessary follow-up to prove the model's applicability more broadly. However, the implementers of medical calculators do not necessarily wait for validation studies before making a calculator available on their platform.

Once the foundation of the basic input and output types was laid, it was then possible to classify the calculators themselves. We found that medical calculators encompass four distinct types: medical equations, clinical calculators, decision trees, and questionnaires. Each of these types are defined by the form and availability of data they take as input, how the output is presented, and whether the target user is a clinician or a patient. We then cataloged all of the calculators under study and discussed the rates at which each type of calculator occurred. What we found is that clinical criteria make up the majority of cataloged calculators, followed by medical equations. As discussed in section 2.1, the automatic provisioning of CDS had a positive impact on the adoption rate, yet the most implemented type of calculator is not positioned well for automation due to the input types it requires. The automatability of a calculator is also related to the integration ability of a calculator. Integration of a calculator that cannot be fully automated still provides some benefits, such as eliminating the need to log in or use another application, yet it still leaves the barrier and cognitive load of a clinician searching for, finding, and entering relevant clinical factors into a calculator. This is problematic because it not only represents a barrier to use (as we discussed in Chapter 3), but also presents an opportunity for error to be introduced during the process of copying data from one place to another.

Finally, we investigated literature references in the implementations of medical calculators. We found that clinical criteria calculators were referenced over 90% of the time, but medical equations were referenced less than 70% of the time for the calculators that were cataloged. Access to the explanation of a calculator's result is becoming increasingly important as lawmakers begin to ponder the effects of artificial intelligence on human life, and some jurisdictions are passing laws requiring artificial intelligence output to be explainable [112]. In our analysis of reference links provided by implemented calculators, we found that full-text references were not available without a subscription. To the degree that an abstract can provide the necessary background for explaining the results of a calculator this may not be an issue, but it does severely limit the dissemination of new medical evidence. Another limitation is the apparent 9-year lag between publication and implementation of medical calculators. This is consistent with other studies showing similar lags of 17 [14] to 24 years [15] before mainstream adoption of new medical evidence. This kind of lag implies that medical calculators, while potentially well-positioned to integrate medical evidence within clinician workflow, would be unable to provide new medical evidence without first addressing this apparent lag. This also means that implemented medical calculators may be out of date with more current evidence.

5.3 Use and Perceptions of Usefulness of CDS by Clinicians

Chapter 3 further investigated the role that medical calculators play in clinical practice through a survey of 819 physicians and residents. The goals of this survey were to study the role that EHR integration plays in the use or non-use of medical calculators, and what factors might limit the use and perceived usefulness of calculators. We found that as experience goes up, the probability of calculator use goes down. Clinicians with less experience use CDS at a much higher rate than experienced clinicians. In free-text responses resident physicians described that using calculators helped them feel more confident about their decisions. More experienced clinicians felt calculators were unnecessary for patient care, which suggests that experienced clinicians relied on their experience over the use of CDS. Interestingly, 83% of the respondents who indicated non-use of calculators reported that using medical calculators could positively affect patient care, even though they chose not to use them. More than half of medical calculator users indicated that they became more efficient by using them, and conversely, efficiency would suffer if they were not available, indicating that calculator use has become a part of their clinical workflow.

We also identified a dichotomy in which non-users recognized the potential for positive benefit of medical calculators but chose not to use them. A lack of perceived need was the most common reason indicated for not using calculators, and the top barrier identified in the survey was not having calculators integrated into the EHR. Lack of integration as a factor leading to lower adoption of CDS is consistent with the results of prior studies which is discussed in Chapter 2. Perceptions of calculators not being necessary underscore a more difficult and persistent problem to be solved, that of a lack of trust in CDS, the corollary of which is clinicians placing more trust in their own experience.

Between calculator users and non-users, integration and necessity were the two barriers identified in the survey that differed significantly in the rate of responses. 47% of calculator non-users felt medical calculators were not necessary for patient care but only about 8% of calculator users felt that calculators were not necessary. Conversely, EHR integration for users was reported as a barrier 44% of the time, whereas non-users saw it as a barrier 13% of the time. This suggests that merely integrating CDS into the EHR will not promote adoption without also tackling the deeper (and more challenging) issue of the perception of need.

5.4 Impact of CDS on Patient Outcomes

In Chapter 4 we brought the discussion of CDS full circle by studying the impacts and uses of an EHR-integrated pain management CDS. The study of this particular CDS was notable because its use was not prescribed. Clinicians who used this CDS used it because they found it useful, and not because it was part of a study protocol. Further insulating the actual use of the CDS from the research was the novel use of EHR activity logs to determine use of the CDS which eliminated observed and observer bias and increased the number of patients whose outcomes could be measured.

A primary discovery was that nurses made up the vast majority of the users of the CDS, at nearly 84% of all views. Unlike previous studies related to pain management CDS which were targeted specifically at physicians, this CDS was available to anyone with access to a patient chart. As nurses make up the front lines of patient interaction and pain monitoring and management, this comes as no surprise.

A number of additional positive and negative results were also discovered when assessing patient outcomes. Importantly, a statistically significant lower pain score was achieved when clinicians used the CDS. The difference is below the threshold considered clinically significant by some studies; nevertheless the CDS lowered the mean pain score below the threshold for intervention (greater than 3) when comparing use/non-use groups and pre- and post-first CDS use groups. These differences are meaningful because they highlight that a CDS can have a positive effect on important patient outcomes and the operational efficiency and quality of an organization.

In addition to the pain score, we also examined the effects the CDS had on the prescription of pain medications and opioid antidotes. We found evidence that use of the

CDS was associated with fewer pain medication-related changes per day, with a mean reduction of one medication change per day for patients in the CDS use group. This is a significant finding because it may point to a more stable pain medication regimen with fewer changes necessary to maintain adequate pain control. However, when looking at the important issue of opioid use and overdose, we found no significant difference in the rates of prescription opioid medications at discharge, nor did we find a difference in the ordering of opioid antidotes.

We suggested that adequate control of pain may require the use of opioids for these conditions, and also point out that the clinical guidelines for pancreatitis, one of the diagnoses in the study, call specifically for treatment with opioids. We surmise that physicians, having likely not interacted with the CDS, would be more likely to prescribe a commonly used discharge order set for the condition which may include opioids rather than to create a new order set based on a specific patient's pain experience. This is especially germane because the CDS itself makes no recommendations on discharge analgesics, a factor which we have discussed as reducing adoption. In this case, the adoption rate by physicians was exceptionally low, possibly because the CDS did not provide value in making recommendations on an analgesic regimen.

5.3 Summary and Future Directions

In summary, this study has highlighted the importance of addressing specific qualities of CDS when implementing them within an EHR, with generalizable insights that reach beyond medical calculators and pain management. Development of integrated CDS must be done thoughtfully and with certain well-studied factors in mind if adoption is to be expected. While technologies have emerged to ease the creation of EHR agnostic tools such as decision support, they do not automatically provide for the basic fundamentals of presenting good decision support to clinicians as highlighted in the CDS five rights: the right information to the right person, in the right format, through the right channel, and at the right time. Providing advice, automatic calculation, and integration into the workflow are important topics to consider when developing CDS. As we discovered, not all data used by CDS is available from the EHR. Decisions made during the research process, such as the source of the data used to train predictive models, may have unintended consequences for the adoptability of CDS that result from research.

As the feasibility and popularity of new machine learning methods such as deep learning and other “black box” approaches increase, it will be even more important to design research studies and model development with implementation factors in mind. In addition, access to explanations of CDS results will become more challenging, as black box models do not lend themselves well to the self-evident deciphering of relative feature importance such as one finds with a regression model. Access to primary literature will be important but may not be enough to overcome distrust in the output from hidden models. Future research in the area of CDS will need to focus on these important issues in order to move the field of AI deeper into the medical world. Presentation of results, simple and quick visualizations of model explanations, proper integration at the right time and for the right person, validation of AI models, and practical clinical use are all areas for future research on explainable AI and clinical decision support.

APPENDIXES

Appendix Page

Appendix A

A Survey Instrument

The survey for Chapter 3 was conducted electronically and questions presented to participants were adapted based on responses to previous questions. This is a text representation of the complete contents of the survey, although not every participant was presented with every question.

Medical Calculators Survey

What is the study about? You are invited to participate in a research study being conducted for a dissertation at University of Missouri in Columbia, MO. The researcher is interested in your opinions about medical calculators. You were selected to participate in the study because you currently practice medicine at MU Healthcare. There is no deception in this study.

What will be asked of me? You will be asked to answer some questions in an online survey regarding your feelings about medical calculators. Please answer the questions in the survey as they apply to your experiences. It is estimated that the survey will take 5-10 minutes of your time.

Who is involved? The following people are involved in this research project and can be contacted at any time through email. The principal researcher or the chair would be happy to answer any questions that may arise about the study. Please direct any questions or comments to:

Principal Researcher: Tim Green greentim@health.missouri.edu

Dissertation Chair: Dr. Chi-Ren Shyu shyuc@missouri.edu

Are there any risks? There are no known risks in this study. You may stop the study at any time.

What are some benefits? There are no direct benefits to you for participating in this research. No incentives are offered. The results have scientific interest that may eventually have benefits for the improvement in the delivery of medical calculators and related literature.

Is the study confidential? The data collected in this study are confidential. Only the researchers in this study will see the data and the data will be stored on a secure encrypted server.

Can I stop participating in the study? You have the right to withdraw from the study at any time without penalty.

What if I have questions about my rights as a research participant or complaints? If you have questions about your rights as a research participant, any complaints about your participation in the research study, or any problems that occurred in the study, please contact the researchers identified above. Or, if you prefer to talk to someone outside the study team, you can contact the University of Missouriâ€™s Institutional Review Board at hsirb@missouri.edu, or by calling 573-882-3181

Gender	◯ Female ◯ Male
Role	◯ Attending ◯ Resident ◯ Fellow ◯ Other
Other:	______________________________
Years of Medical Experience	◯ 1 ◯ 2 ◯ 3 ◯ 4 ◯ 5 ◯ 6 ◯ 7-10 ◯ 11-20 ◯ >20

Do you use medical calculators such as Anion Gap, Pneumonia Severity Score, Apgar Score, or similar?	◯ Yes ◯ No
For what reasons do you choose not to use medical calculators?	☐ Too hard to use ☐ Too time consuming ☐ Too complicated ☐ Services/apps cost too much ☐ They are unnecessary for patient care ☐ I didn't know about them ☐ Other
Other:	__________________________________

How do you access the calculators you use?

☐ Website
☐ Smartphone app
☐ Manual chart/nomogram
☐ Integrated Calculators component in PowerChart
☐ Other

Other: ______________________________

Do you pay for a commercial service or app?

○ Yes
○ No

Please list the commercial services/apps you use for medical calculators: ______________________________

Please list the 5 most common conditions or problems that you use calculators for:

How often do you use medical calculators?

◯ Never ◯ Rarely ◯ Occasionally ◯ Regularly ◯ Constantly

Do you maintain a list of favorite calculators?	◯ Yes ◯ No
About how many distinct calculators do you use on a regular basis?	◯ none ◯ 1 or 2 ◯ 3-5 ◯ 5-10 ◯ 10-20 ◯ more than 20
What kind of medical calculators do you prefer?	☐ equations based on discrete values from the patient's chart ☐ questionnaires that may ask about medical history of the patient ☐ decision trees that walk you through a set of questions to arrive at a recommended action

How frequently do you use calculators as part of a patient visit (either planning, during the visit, or when documenting the visit)?

○ Never ○ Rarely ○ Occasionally ○ Regularly ○ Every time

When do you typically use calculators?

☐ Before I see the patient
☐ While I am talking to the patient
☐ After the patient visit is over

How often do you document the results of a calculator in a note?

○ Never ○ Rarely ○ Occasionally ○ Regularly ○ Every time

How often do you take into account the results of a medical calculator when deciding on a plan of care?

○ Never ○ Rarely ○ Occasionally ○ Regularly ○ Every time

Do you feel that the use of calculators positively affects the outcome of a patient?	◯ Yes ◯ No
Do you feel that the use of calculators could positively affect the outcome of a patient?	◯ Yes ◯ No
At what point in patient care do you think using medical calculators has the most positive impact on patient outcomes?	◯ Before I see the patient ◯ While I am talking to the patient ◯ After the patient visit is over

How difficult is it to get data necessary for a calculator out of the EMR?

○ Very Difficult ○ Somewhat Difficult ○ Neither Easy nor Difficult ○ Somewhat Easy
○ Very Easy

If medical calculators were integrated with PowerChart, how likely would you be to use them?

○ Very Unlikely ○ Somehwat Unlikely ○ Neither Unlikely or Likely ○ Somewhat Likely
○ Very Likely

How does using medical calculators impact the efficiency of your work?

- ◯ More Efficent
- ◯ No Difference
- ◯ Less Efficient

How does documenting the results of a medical calculator you've used impact the efficiency of your work?

- ◯ More Efficent
- ◯ No Difference
- ◯ Less Efficient
- ◯ I do not document the use of medical calculators

How does the unavailability of a medical calculator you normally use impact your efficiency?

- ◯ More Efficent
- ◯ No Difference
- ◯ Less Efficient

How do you find out about new medical calculators?

- ☐ Online services e.g. Up To Date, eMedicine
- ☐ Online journals
- ☐ Print publications
- ☐ Colleagues
- ☐ Grand rounds
- ☐ Conferences
- ☐ Other

Other: ______________________________

How likely are you to use newly published medical calculators?

○ Very Unlikely ○ Somehwat Unlikely ○ Neither Unlikely or Likely ○ Somewhat Likely
○ Very Likely

How likely are you to use calculators based on newer literature versus older calculators that perform the same function?

○ Very Unlikely ○ Somehwat Unlikely ○ Neither Unlikely or Likely ○ Somewhat Likely
○ Very Likely

How long do you typically wait before adopting a new medical calculator once it's been published?

- ○ I use them as soon as I learn about them
- ○ I wait 1-6 months
- ○ I wait 6 months to a year
- ○ I wait 1 to 5 years
- ○ I wait more than 5 years

Who determines the calculators you use for patient care?	◯ I do ◯ My department ◯ The institution ◯ I don't know ◯ Other
Other:	________________________________

Please describe any barriers that exist that prevent you from using medical calculators more.

What features are lacking with existing medical calculator products?

What features do you like the most about existing medical calculator products?

Appendix B

B Detailed Survey Results

Survey questions and response rates by Question Domain. "n/a" indicates the question was not asked of that group.

Question Domain: Demographics – Collect basic demographic information about participants.			
Do you use medical calculators?	**no**	**yes**	**Total**
	26.85% (29)	73.15% (79)	100% (108)
Gender			
female	31.03% (9)	39.24% (31)	37.04% (40)
male	68.97% (20)	60.76% (48)	62.96% (68)
Role			
attending	79.31% (23)	60.76% (48)	65.74% (71)
fellow	3.45% (1)	5.06% (4)	4.63% (5)
other	10.34% (3)	8.86% (7)	9.26% (10)
resident	6.9% (2)	25.32% (20)	20.37% (22)
Years Experience			
1-6	10.34% (3)	43.04% (34)	34.26% (37)
7-20	27.59% (8)	35.44% (28)	33.33% (36)
>20	62.07% (18)	21.52% (17)	32.41% (35)
Question Domain: Frequency of Use – Assess frequency and timing of use			
How often do you use medical calculators?			
Never | Rarely	n/a	3.8% (3)	
Occasionally	n/a	34.18% (27)	
Regularly | Constantly	n/a	62.03% (49)	
How frequently do you use calculators as part of a patient visit (either planning, during the visit, or when documenting the visit)?			
Never | Rarely	n/a	10.13% (8)	
Occasionally	n/a	54.43% (43)	
Regularly | Every time	n/a	35.44% (28)	
When do you typically use calculators? (choose multiple)			

After the patient visit is over	n/a	58.23% (46)
Before I see the patient	n/a	45.57% (36)
While I am talking to the patient	n/a	37.97% (30)

Question Domain: Nature of Use – Assess the way in which calculators are used

How do you access the calculators you use? (choose multiple)

Integrated Calculators component in PowerChart	n/a	24.05% (19)
Manual chart/nomogram	n/a	17.72% (14)
Other	n/a	1.27% (1)
Smartphone App	n/a	75.95% (60)
Website	n/a	70.89% (56)

Do you maintain a list of favorite calculators?

no	n/a	62.03% (49)
yes	n/a	37.97% (30)

About how many distinct calculators do you use on a regular basis?

1 or 2	n/a	50.63% (40)
10-20	n/a	2.53% (2)
3-5	n/a	39.24% (31)
5-10	n/a	6.33% (5)
none	n/a	1.27% (1)

What kind of medical calculators do you prefer? (choose multiple)

decision trees that walk you through a set of questions to arrive at a recommended action	n/a	25.32% (20)
equations based on discrete values from the patient's chart	n/a	86.08% (68)
questionnaires that may ask about medical history of the patient	n/a	18.99% (15)

Who determines the calculators you use for patient care?

I do	n/a	87.34% (69)
I don't know	n/a	6.33% (5)
My department	n/a	1.27% (1)
Other	n/a	3.8% (3)
The institution	n/a	1.27% (1)

Question Domain: Meaningful Use – Assess the use of calculators in a meaningful way, related to the US HITECH act

How often do you document the results of a calculator in a note?

Never | Rarely	n/a	8.86% (7)
Occasionally	n/a	34.18% (27)
Regularly | Every time	n/a	56.96% (45)

How often do you take into account the results of a medical calculator when deciding on a plan of care?			
Never | Rarely	n/a	2.53% (2)	
Occasionally	n/a	30.38% (24)	
Regularly | Every time	n/a	67.09% (53)	
Question Domain: Perceived Usefulness – Understand the way in which calculator users feel they impact patient care			
For what reasons do you choose not to use medical calculators? (choose multiple)			
I didn't know about them	27.59% (8)	n/a	
Other	27.59% (8)	n/a	
Services/apps cost too much	0.0% (0)	n/a	
They are unnecessary for patient care	41.38% (12)	n/a	
Too complicated	10.34% (3)	n/a	
Too hard to use	3.45% (1)	n/a	
Too time consuming	13.79% (4)	n/a	
Do you feel that the use of calculators could positively affect the outcome of a patient?			
no	17.24% (5)	n/a	
yes	82.76% (24)	n/a	
Do you feel that the use of calculators positively affects the outcome of a patient?			
no	n/a	5.06% (4)	
yes	n/a	94.94% (75)	
At what point in patient care do you think using medical calculators has the most positive impact on patient outcomes?			
After the patient visit is over	n/a	28.0% (21)	
Before I see the patient	n/a	33.33% (25)	
While I am talking to the patient	n/a	38.67% (29)	
Question Domain: EHR Integration – Questions related to integration of calculators in EHR			
How difficult is it to get data necessary for a calculator out of the EMR?			
Neither Easy nor Difficult	n/a	31.65% (25)	
Somewhat Easy | Very Easy	n/a	32.91% (26)	
Very Difficult | Somewhat Difficult	n/a	35.44% (28)	
If medical calculators were integrated with PowerChart, how likely would you be to use them?			
Neither Unlikely or Likely	10.34% (3)	3.8% (3)	5.56% (6)
Somewhat Likely | Very Likely	62.07% (18)	92.41% (73)	84.26% (91)
Very Unlikely | Somewhat Unlikely	27.59% (8)	3.8% (3)	10.19% (11)
Question Domain: Efficiency – Assess the impact medical calculators have on work efficiency			
How does using medical calculators impact the efficiency of your work?			
Less Efficient	n/a	16.46% (13)	

More Efficient	n/a	60.76% (48)	
No Difference	n/a	22.78% (18)	
How does documenting the results of a medical calculator you've used impact the efficiency of your work?			
I do not document the use of medical calculators	n/a	3.8% (3)	
Less Efficient	n/a	21.52% (17)	
More Efficient	n/a	36.71% (29)	
No Difference	n/a	37.97% (30)	
How does the unavailability of a medical calculator you normally use impact your efficiency?			
Less Efficient	n/a	69.62% (55)	
More Efficient	n/a	7.59% (6)	
No Difference	n/a	22.78% (18)	
Question Domain: Awareness – General awareness about medical calculators			
How do you find out about new medical calculators? (choose multiple)			
Colleagues	55.17% (16)	51.9% (41)	52.78% (57)
Conferences	27.59% (8)	25.32% (20)	25.93% (28)
Grand rounds	13.79% (4)	17.72% (14)	16.67% (18)
Online journals	10.34% (3)	21.52% (17)	18.52% (20)
Online services e.g. Up To Date, eMedicine	34.48% (10)	68.35% (54)	59.26% (64)
Other	20.69% (6)	6.33% (5)	10.19% (11)
Print publications	20.69% (6)	17.72% (14)	18.52% (20)
How likely are you to use newly published medical calculators?			
Neither Unlikely or Likely	n/a	24.05% (19)	
Somewhat Likely | Very Likely	n/a	59.49% (47)	
Very Unlikely | Somewhat Unlikely	n/a	16.46% (13)	
How likely are you to use calculators based on newer literature versus older calculators that perform the same function?			
Neither Unlikely or Likely	n/a	41.77% (33)	
Somewhat Likely | Very Likely	n/a	50.63% (40)	
Very Unlikely | Somewhat Unlikely	n/a	7.59% (6)	
How long do you typically wait before adopting a new medical calculator once it's been published?			
I use them as soon as I learn about them	n/a	40.51% (32)	
I wait 1 to 5 years	n/a	10.13% (8)	
I wait 1-6 months	n/a	24.05% (19)	
I wait 6 months to a year	n/a	21.52% (17)	
I wait more than 5 years	n/a	3.8% (3)	

Question Domain: Usability – Capture free text responses related to the usability of calculators			
Please describe any barriers that exist that prevent you from using medical calculators more.			
UI	13.33% (2)	2.56% (1)	5.56% (3)
integration	13.33% (2)	43.59% (17)	35.19% (19)
necessity	46.67% (7)	7.69% (3)	18.52% (10)
none	0.0% (0)	20.51% (8)	14.81% (8)
technical	0.0% (0)	5.13% (2)	3.7% (2)
training	13.33% (2)	2.56% (1)	5.56% (3)
workflow	13.33% (2)	17.95% (7)	16.67% (9)
no response	48.28% (14)	50.63% (40)	50.0% (54)
What features are lacking with existing medical calculator products?			
UI	14.29% (2)	0.0% (0)	4.44% (2)
integration	7.14% (1)	61.29% (19)	44.44% (20)
none	50.0% (7)	29.03% (9)	35.56% (16)
other	7.14% (1)	3.23% (1)	4.44% (2)
specific calculator feature	21.43% (3)	6.45% (2)	11.11% (5)
no response	51.72% (15)	60.76% (48)	58.33% (63)
What features do you like the most about existing medical calculator products?			
UI	0.0% (0)	8.33% (3)	6.38% (3)
comprehensiveness	0.0% (0)	5.56% (2)	4.26% (2)
ease of use	0.0% (0)	41.67% (15)	31.91% (15)
integration	0.0% (0)	13.89% (5)	10.64% (5)
none	72.73% (8)	5.56% (2)	21.28% (10)
other	9.09% (1)	13.89% (5)	12.77% (6)
speed	18.18% (2)	11.11% (4)	12.77% (6)
no response	62.07% (18)	54.43% (43)	56.48% (61)

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VITA

Tim Green received his Bachelors of Science in Computer Science in 1994 from Northwest Missouri State University. He began studying in the PhD program of the University of Missouri Institute for Data Science and Informatics in August of 2013. His doctoral research focused on the practical applications of clinical decision support. He received a PhD in Informatics with a focus on Health Informatics in December of 2019.

He is a member of the American Medical Informatics Association, and as a student was a member of a finalist team in 2016 for that association's Student Design Challenge. Additionally, his paper in the MedInfo 2019 conference was a finalist for best student paper. His work experience includes 25 years working in industry for government, small business, and startups in various fields, including public health, hospitals, e-commerce, and construction. Additionally, he has taught at the post-secondary level for technical schools as well as at the University of Missouri Data Science and Analytics program. His research interests include clinical decision support implementations and patient centered outcomes.