MEDINFO 2019: Health and Wellbeing e-Networks for All
L. Ohno-Machado and B. Séroussi (Eds.)

doi:10.3233/SHTI190293

Developing a Taxonomy of Online Medical Calculators for Assessing Automatability and Clinical Efficiency Improvements

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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.

Keywords:
Medical Calculator; Clinical Decision Support Systems.

Introduction

Electronic health records (EHR) are becoming highly prevalent in hospital systems [1]. Clinical decision support (CDS) within EHRs is also ubiquitous. Technologies such as the SMART platform [2], the HL7 FHIR data interface [3], and CDS Hooks [4] 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 [5,6]; however, these benefits are not universal for all CDS [7,8].

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 [9]. 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 on 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 [10,11]. Appropriate integration of CDS has been problematic, with alert fatigue being well studied [12,13]. Recent studies have investigated the potential for automating calculation of medical calculators, highlighting the opportunities and challenges of doing so [14,15].

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 [16]. The automatic provisioning of CDS can have a positive impact on important healthcare issues, such as patient safety [17], racial and gender disparities [18], and process adherence [19]. In addition, prior studies show that factors such as automatic provisioning of CDS tools [6,20] can impact the adoption and success of CDS. Moreover, the Kawamoto study [21] 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 [16], while Berlin et al. developed a framework for the classification of CDS (the CDSS Taxonomy framework) [22]. Calculator inputs and outputs have not been well studied. Dziadzko et al. [23] 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. [15] 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.

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.

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.

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.

Calculator Output

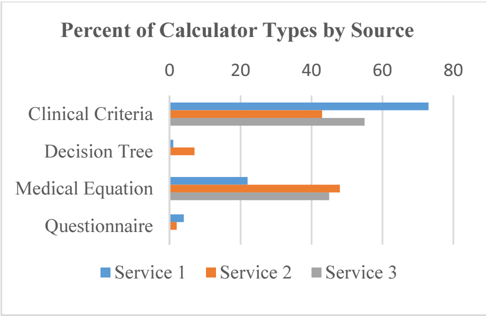
For demand-driven calculators, the way in which calculator results are delivered (Recommendation Explicitness [22]) were considered germane in our review as they are related to the advisory nature of the calculator output. Advisory calculators suggest a diagnosis or recommendation, and non-advisory are 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 I showing the distribution of these.

1. Diagnosis - Calculator presents a potential diagnosis, for example the Duke Criteria for Infective Endocarditis [24] 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 [25] 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 [26] provides a probability of mortality
4. Classification - Calculator classifies patient in one or more categories. For example, the Apgar Score [27] 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.

Kawamoto [21] 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%

Table I - 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

a) 

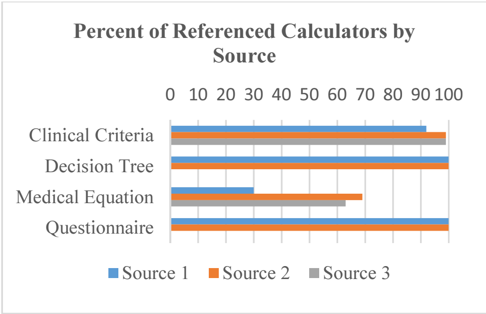
b) 

Figure 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.

(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.

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 [28] accepts discrete data input. The Wells Score System for Deep Vein Thrombosis [29] 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 [30] has input with logical computation on discrete data elements (M Protein: IgG > 3.5 g/L). The Head CT Rule for Minor Head Injury [31] 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 [32]: "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 [33].
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 [34], 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 [35] is an example of a decision tree.

Figure 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.

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" [22]. 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 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.

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). 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

Table 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

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.

An analysis of the publication year of the NCBI references supported a trend towards older publications (Figure 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 [36] to 24 years [37].

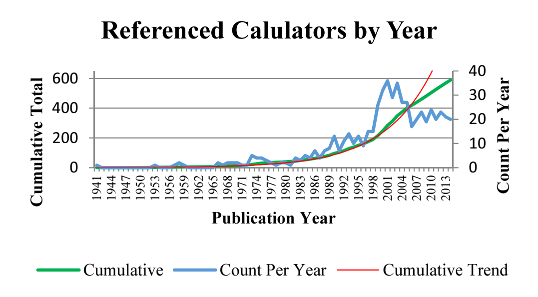


Figure 2 – Number of referenced calculators by year.

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 [21]. 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- this is 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 [21]. 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.

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 [38] and the creation of "npj Digital Medicine" [39], 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.

Acknowledgments

This study was supported by the Shumaker Endowment for Biomedical Informatics. The authors wish to thank Dr. Thomas Selva, MD and Dr. Stevan Whitt, MD for their support and guidance. The authors have no conflicts of interest to declare.

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