Automating Clinical Score Calculation within the Electronic Health Record

A Feasibility Assessment

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Summary

Objectives: Evidence-based clinical scores are used frequently in clinical practice, but data collection and data entry can be time consuming and hinder their use. We investigated the programmability of 168 common clinical calculators for automation within electronic health records.
Methods: We manually reviewed and categorized variables from 168 clinical calculators as being extractable from structured data, unstructured data, or both. Advanced data retrieval methods from unstructured data sources were tabulated for diagnoses, non-laboratory test results, clinical history, and examination findings.
Results: We identified 534 unique variables, of which 203/534 (37.8%) were extractable from structured data and 269/534 (50.4.7%) were potentially extractable using advanced techniques. Nearly half (265/534, 49.6%) of all variables were not retrievable. Only 26/168 (15.5%) of scores were completely programmable using only structured data and 43/168 (25.6%) could potentially be programmable using widely available advanced information retrieval techniques. Scores relying on clinical examination findings or clinical judgments were most often not completely programmable.
Conclusion: Complete automation is not possible for most clinical scores because of the high prevalence of clinical examination findings or clinical judgments – partial automation is the most that can be achieved. The effect of fully or partially automated score calculation on clinical efficiency and clinical guideline adherence requires further study.

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1. Background and Significance

Scoring is a part of modern medical practice. In general, scores have been created to predict clinical outcomes, perform risk stratification, aid in clinical decision making, assess disease severity or assist diagnosis. Methods used for scoring range from simple summation to complex mathematical models. After score creation, several factors limiting generalized usage have been identified: lack of external validation, failure to provide clinically useful predictions, time-consuming data collection, complex mathematical computations, arbitrary categorical cutoffs for clinical predictors, imprecise predictor definitions, usage of non-routinely collected data elements, and poor accuracy in real practice [1]. Even among scores accepted by clinicians in clinical practice guidelines, these same weaknesses can still be still barriers to consistent, widespread use [2–5]. Identifying methods to overcome these weaknesses may help improve evidence-based clinical practice guideline adherence and patient care [1].

Score complexity can be a barrier to manual score calculation, especially given the time constraints of modern clinical practice. For example, the Acute Physiology and Chronic Health Evaluation (APACHE) score, widely accepted in critical care practice, consisted of 34 physiologic variables in its original iteration. Data collection and calculation is time-consuming, therefore subsequent APACHE scoring models (APACHE II and III) were simplified to include fewer variables to increase usage [6–8]. Fewer variables also reduced the risk of missing data elements. Other popular scores, such as $CHADS_2$ and HAS-BLED, have employed mnemonics and point-based scoring systems for ease of use at the point-of-care [9, 10]. Despite these simplifications to support manual calculation, many popular and useful clinical scores have been translated to mobile and web-based calculators for use at the bedside [11–13]. The use of mobile clinical decision support tools at the point-of-care is a promising development, however these tools largely remain isolated from the clinical data present in the Electronic Health Record (EHR) [14].

In 2009, Congress passed the Health Information Technology for Economic and Clinical Health Act, which aimed to stimulate EHR adoption by hospitals and medical practices. As a result, by the end of 2014, 96.9% of hospitals were using a certified EHR and 75.5% were using an EHR with basic capabilities [15]. Concurrent with widespread EHR adoption, there has been a renewed emphasis on clinical quality and safety and the practice of evidence-based medicine. Integration of useful evidence-based clinical score models into the EHR with automated score calculation based on real-time data is a logical step towards meaningful use of EHR's to improve patient care. Time-motion studies of hospitalists and emergency department physicians have shown that they spend about 34% and 56% of their time interacting with the EHR, respectively [16, 17]. Automation of common, recurrent clinical tasks may reduce the time clinicians spend in front of the computer performing data retrieval or data entry. Potential benefits are twofold – allowing clinicians to spend more time at the bedside and reducing error associated with data entry [18].

2. Objectives

The goal of this study was to quantify the "programmability" (defined as the opportunity to automate calculation through computerized extraction of clinical score components) of validated clinical scores.

3. Methods

3.1 Calculator identification

This study was performed at Mayo Clinic in Rochester, Minnesota and was deemed exempt by the Institutional Review Board. One hundred and sixty-eight externally validated clinical scores published in the medical literature were identified as described previously [19]. In brief, we extracted online clinical calculators from twenty-eight dedicated online medical information resources [11–13, 20]. A total of 371 calculators were identified; two-hundred three calculators were excluded from this analysis because they consisted of simple formula or conversions. Only validated clinical scores published in PubMed were included in our analysis.

3.2 Score variable classification

Data variables for the remaining 168 calculators were tabulated and categorized as being theoretically retrievable from structured or unstructured EHR data sources. We defined structured EHR data sources as objective data present in the EHR in a retrievable, structured format. Examples include: laboratory values (e.g. "creatinine"), ICD-9-CM or ICD-10-CM coded diagnoses (e.g. "atrial fibrillation"), medications (e.g. "Preoperative treatment with insulin"), demographic values (e.g. "age"), vital signs (e.g. "heart rate"), and regularly charted structured data (e.g. "stool frequency"). Unstructured EHR data sources included subjective variables, such as descriptive elements of clinical history, examination findings (e.g. "withdraws to painful stimuli"), non-laboratory test results (e.g. "echocardiogram findings"), and clinical judgments entered into the EHR (e.g. "cancer part of presenting problem"). Variable categorization was not exclusive - some data elements could potentially be found in both structured and unstructured data sources depending on the clinical context.

3.3 Programmability analysis

Two definitions of programmability were used in our analysis. We defined basic programmability as the proportion of variables in each score for which calculation is possible using only structured or numerical data found in the EHR. Advanced programmability was defined as the proportion of variables within each score potentially retrievable by a combination of structured data or advanced information retrieval techniques. A summary of our review process is shown in ►Figure 1.

First, to assess the basic programmability of each score, we compared each variable against a list of structured data elements available in our local EHR. Next, two reviewers with local experience in automated score calculator creation (CA and MD) manually reviewed each variable to assess if two advanced information retrieval techniques, Boolean logic text search or natural language processing (NLP) [21], could theoretically be utilized to abstract the following specific clinical variable categories when structured data was not present: diagnoses, non-laboratory test results (e.g. procedure reports, radiology reports), and clinical history. We interpreted the availability of each variable in the clinical context of each score's target population; clinical examination findings were assumed to be unextractable. Disagreement on the ability to capture each score's variables using advanced information retrieval techniques was completely adjudicated between the reviewers. Descriptive statistical methods were used. All statistical analyses were performed with R version 3.1.1 [22].

4. Results

We identified five-hundred thirty-four unique variables in 168 clinical scores. The five most utilized variables were "Age" (n = 83), "Heart rate" (n = 34), "Systolic blood pressure" (n = 34), "Creatinine/eGFR" (n = 31) and "Sex" (n = 27). A summary of categorization is as follows: 25/534 (4.7%) vital signs, 7/534 (1.3%) demographic variables, 97/534 (18.2%) coded diagnoses or procedures, 131/534 (24.5%) history of present illness, 91/534 (17.0%) laboratory values, 20/534 (3.7%) medications, 133/534 (24.9%) clinical examination, 106/534 (19.9%) clinical judgment, 29/534 (5.4%) another clinical score, 75/534 (14.0%) non-laboratory test result, 40/534 (7.5%) non-vital sign regularly charted variables. Categorization was not mutually exclusive: 360/534 (67.4%) were assigned to one category, 136/534 (25.5%) to two categories and 38/534 (7.1%) to three or more categories.

Structured data sources were available for 202/534 (37.8%) variables. Using a combination of structured data and advanced information retrieval techniques, the proportion of variables theoretically retrievable increased to 269/534 (50.4%). About half of variables, 265/534 (49.6%), rely on data existing outside of the EHR and cannot be reliably extracted. Basic and advanced programmability assessments for all 168 scores can be found in ►Table 1 and ►**Supplemental Table** 1. For brevity, ►Table 1 only lists scores with greater than 85% advanced programmability. Only 26/168 (15.5%) scores were 100% programmable using solely structured data and 43/168 (25.6%) were potentially

100% programmable when supplemented with advanced information retrieval methods. Non-programmable data elements included clinical examination findings, clinical judgments, radiology findings, and planned procedures. Representative examples of non-programmable data elements can be found in ►Table 2. We have described the individual scores evaluated in our study further in ►Supplemental Table 1. The supplemental table includes the PubMed ID, clinical outcomes predicted, applicable populations extracted from the derivation study, variables, and programmability assessments for each score.

5. Discussion

In this study, we analyzed the theoretical programmability of 168 common, evidence-based clinical score calculators available online to explore the feasibility of automated score calculators integrated into the EHR. In general, variable values can be extracted from either structured or unstructured data sources. Methods of information retrieval from unstructured data sources, such as Boolean text search and NLP, may not be available in all EHR systems and success may depend on local expertise. Consequently, we dichotomized our programmability evaluation of each variable into information retrieval methods that either (1) used only structured data ("basic programmability") or (2) used structured data supplemented with information from unstructured data sources ("advanced programmability"). Data elements categorized as structured variables included laboratory values, diagnoses, medications, vital signs and demographic parameters. These parameters are commonly available as structured EHR data elements; availability as structured data is likely to be similar in other settings. Therefore, we would expect wide generalizability of automation methods for clinical scores that utilize only structured data sources.

Although the list of clinical score calculators we analyzed was not comprehensive, all (1) have been externally validated in the medical literature, (2) are found on commonly used medical reference web portals or calculator repositories, and (3) have been paired with calculators to assist score computation and interpretation. Calculator availability through these online sites and apps is driven by consumer demand; most calculator repositories include methods allowing users to request inclusion of additional calculators. Therefore, we believe that the calculators examined in this study reflect most of the in-demand scores used in clinical practice. The programmability of other important scores not included in this study could be determined through a similar process. We also noted a non-significant trend towards increased basic programmability of newer clinical scores (data not shown), potentially reflecting the use of readily available EHR data for model development and validation. If this trend is real, one would expect high programmability of future evidence-based clinical scores – facilitating automation.

Usage of the manual score calculators analyzed by our study requires manual data collection and entry into a web-based service or mobile application. Automating the data collection and entry processes would create time-saving efficiencies; these efficiencies may be larger for scores with cognitively demanding calculations, scores requiring extensive data collection and entry, or scores that are frequently recalculated.[23] Many of the scores evaluated in our analysis have already been successfully automated with minimal modification, including APACHE II, SOFA, PESI [24–28]. In our analysis, we found these scores to be highly programmable. Additionally, these scores were clinically important at the time of automation. We propose that future efforts towards clinical score automation should be directed towards the clinical scores that are both highly utilized and highly programmable. To accomplish this goal, the results of our programmability analysis should be paired with a user-needs assessment to prioritize future work.

Our programmability analysis has several limitations. First, the advanced programmability assessments were theoretical and based on extensive experience with these specific advanced information retrieval methods at our institution. Score calculators requiring advanced information retrieval methods for full automation will likely need further study prior to local implementation.

Second, retrieval of certain variable types may require special considerations. Diagnosis variables can be found in both structured and unstructured data sources within the EHR and linked information systems. The accuracy of diagnosis identification using either diagnosis codes (ICD-9-CM, ICD-10-CM) independently or supplemented with text search or NLP can be suspect - producing many false positives and false negatives [29]. More comprehensive terminologies such as SNOMED CT® (Systemized Nomenclature of Medicine – Clinical Terms) may improve accuracy of diagnosis identification as its usage becomes more widespread by virtue of its comprehensive biomedical vocabulary. Laboratory test values can have multiple naming variations that require reconciliation (e.g. samples measured from serum or plasma). Reconciliation of laboratory test data may be more difficult when using an EHR with remote retrieval capabilities due to different laboratory naming conventions.

Third, many clinical scores rely on time-sensitive clinical data that may be missing from the EHR at the time of score calculation – such as clinical examination findings and clinical history. Furthermore, subjective variable extraction by advanced information retrieval techniques is not 100% accurate. Consequently, calculator interfaces will need to allow for manual entry to correct erroneous data or to input missing data and data from external sources. To give users confidence of data veracity, users may desire a hyperlink to the source data or timestamp of when the source data was obtained.

Lastly, about half of all variables extracted from the clinical scores evaluated in our study are likely not retrievable using either structured data alone or supplemented with advanced information retrieval techniques. Other advanced information retrieval techniques, such as machine learning and data mining, could be used to extract score variables from the EHR or clinical images [30–34]. The application of these techniques may expand the list of fully programmable calculators and increase calculation accuracy. However, even these other advanced techniques will likely not be able to retrieve many variables representing clinical history items, clinical examination findings or clinical judgments – the largest categories of data elements used in the selected clinical scores. Score calculators containing these data elements may require alternative strategies to utilize these non-programmable elements. One potential strategy for semi-automated calculation of scores utilizing non-programmable data elements would be creation of an interface with pre-populated checkboxes or radio-buttons for expected inputs. Other strategies may be needed for scores requiring raw data input, such as patient generated family history information.

6. Conclusion

We assessed one hundred sixty-eight commonly used clinical scores for programmability to facilitate EHR-based automated calculation. Only 26/168 (15.5%) of scores were completely programmable using solely structured data extractable from the EHR and 43/168 (25.6%) could potentially be programmable using widely available advanced information retrieval techniques. Partial automation with manual entry of non-programmable data elements may be necessary for many important clinical scores. The effect of fully or partially automated score calculation on clinical efficiency and clinical guideline adherence requires further study.

Multiple Choice Question

In addition to programmability, which of the following factors is most important to guide the prioritization of automated clinical score calculator development?

A) Disease prevalence
B) Clinician needs
C) Frequency of score calculation
D) Incorporation into clinical practice guidelines

Answer

All of these factors are important considerations when choosing a clinical score to automate. A score calculator for a disease with high prevalence may be used frequently, but only if the predicted outcome is useful to the clinician. Automating a score that requires frequent recalculation would save time, especially if the information retrieval and score calculation tasks are time-consuming. Incorporation of a score into clinical practice guidelines can both elevate the importance of a score and drive utilization. Clinicians are the best suited to understand the local prevalence of disease, the clerical burdens of recalculation, and the relative importance of the score to their practice. Therefore, (B) is the best answer.

Clinical Relevance Statement

Automated calculation of commonly used clinical scores within the EHR could reduce the cognitive-workload, improve practice efficiency, and facilitate clinical guideline adherence.

Conflict of Interest Statement

The authors declare that they have no conflicts of interest in the research.

Human Subjects Protects

Humans subjects were not included in the project.

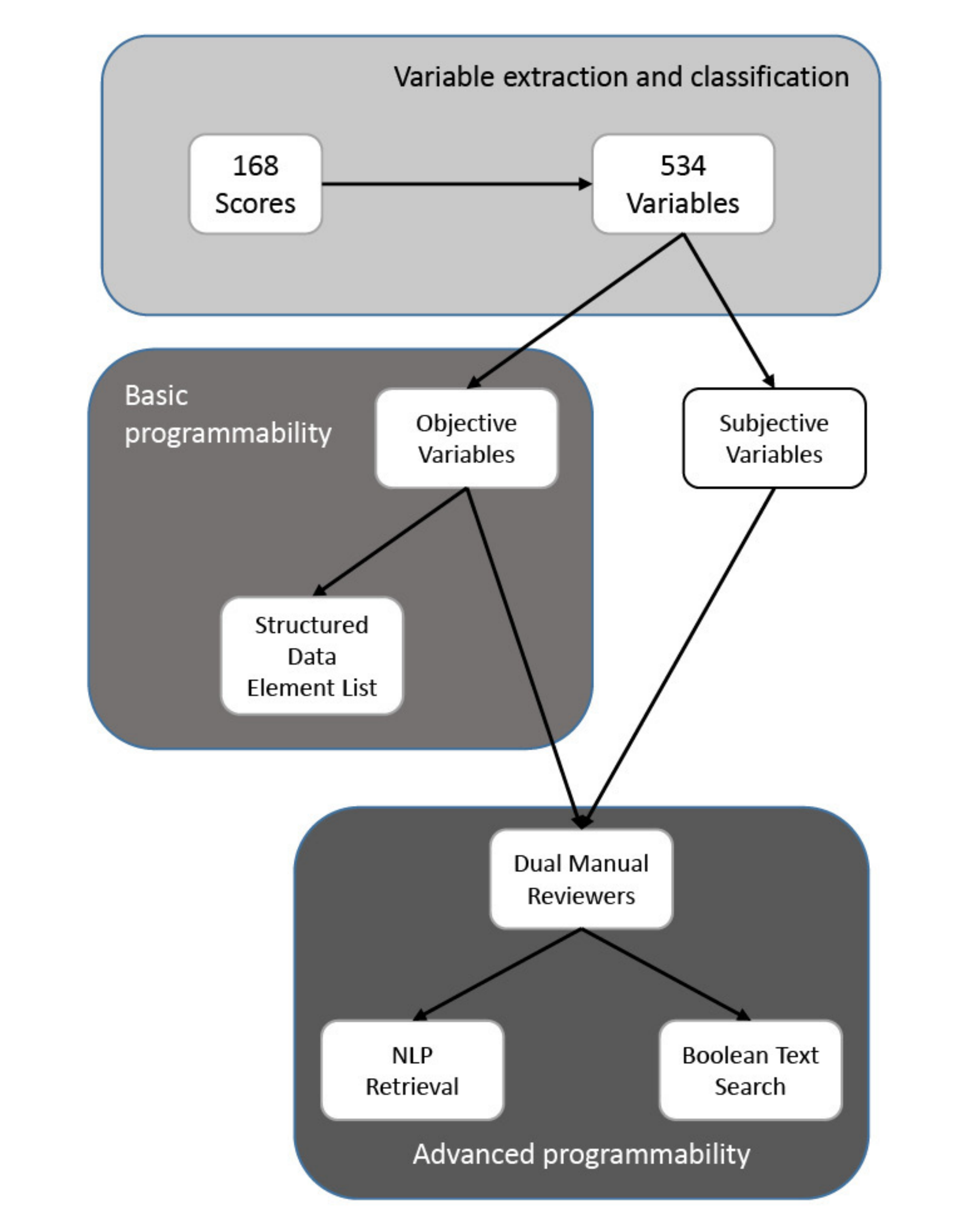

Fig. 1 **Study Methodology.** Variables were extracted from all 168 scores and tabulated. The list of variables was compared against a list of structured variables available in the EHR. Additionally, two reviewers analyzed the theoretical extractability of each variable from the EHR with either NLP or Boolean text search.

Table 1 Programmability of clinical scores.

Score name	Number of variables	Basic programmability (%)	Advanced programmability (%)
Completely programmable using only structured data sources			
ABIC score	4	100	100
ATRIA bleeding risk score	5	100	100
ATRIA stroke risk score	8	100	100
Bleeding risk score	4	100	100
CHA2DS2-VASc	7	100	100
CHADS2	5	100	100
Charlson Comorbidity index	16	100	100
CRIB II	5	100	100
Glasgow alcoholic hepatitis score	5	100	100
JAMA kidney failure risk equation	8	100	100
LODS score	11	100	100
LRINEC Score for Necrotizing STI	6	100	100
MOD score	6	100	100
Oxygenation index	3	100	100
Pancreatitis outcome prediction score	6	100	100
PELD score	5	100	100
Ranson's criteria	11	100	100
RAPS	4	100	100
REMS	6	100	100
Renal risk score	6	100	100
Revised Trauma score	3	100	100
Rockall score	3	100	100
Rotterdam score	4	100	100
SOFA	6	100	100
sPESI	6	100	100
TIMI risk index	3	100	100
Completely programmable with advanced information retrieval methods			
APACHE II	14	93	100
EHMRG	10	90	100
ASCVD pooled cohort equations	9	89	100
HAS-BLED	9	89	100
IgA nephropathy score	8	88	100
Framingham coronary heart disease risk score	7	86	100
SIRS, Sepsis, and Septic Shock criteria	7	86	100
RIETE score	6	83	100
MELD score	5	80	100
SWIFT score	5	80	100
Lung Injury score	4	75	100

Table 1 Continued

Score name	Number of variables	Basic programmability (%)	Advanced programmability (%)
Malnutrition universal screening tool	4	75	100
PIRO score	8	75	100
Panc 3 score	3	67	100
Surgical Apgar score	3	67	100
GAP risk assessment score	4	50	100
Clinical Pulmonary Infection Score	7	43	100
Partial automation, some manual input required			
Qstroke score	16	88	94
SAPS II	16	94	94
PRISM score	14	93	93
MPMII – 24–48–72	13	85	92
QRISK2	13	85	92
PELOD score	12	92	92
30 day PCI readmission risk	11	82	91
PESI	11	91	91
QMMI score	11	82	91
SNAP-PE	31	90	90
Cardiac surgery score	10	60	90
PORT/PSI score	20	85	90
SNAP	28	89	89
Hemorr2hages score	9	89	89
SNAP-PE II	9	89	89
CRUSADE score	8	88	88
SHARF score	8	88	88
MPMII – admission	15	67	87
Mayo Clinic Risk Score – inpatient death after CABG	7	71	86
Mayo Clinic Risk Score – inpatient death after PCI	7	71	86
Mayo Clinic Risk Score – inpatient MACE after PCI	7	71	86
Meningococcal septic shock score	7	71	86
MPM – 24hr	14	86	86
SCORETEN scale	7	86	86

Table 2 Representative sample of non-programmable variables.

Score variable	Score containing variable
Clinical examination	
Wheezing present	Clinical asthma evaluation score – 2, Pulmonary score, Modified pulmonary index score (MPIS), Pediatric asthma severity score (PASS)
Clinical judgment	
Alternative diagnosis as or more likely than deep venous thrombosis	Well's criteria for DVT
Cancer part of the presenting problem	Mortality probability model (MPM-0)
Clinically unstable pelvic fracture	TASH score
Another clinical score	
MMRC dyspnea index	BODE score
MMSE-KC	Multidimensional frailty score
Non-laboratory test result	
Progression of chest radiographic abnormalities	Clinical pulmonary infection score (CPIS)
Pancreatic necrosis	CT severity index
Clinical history	
Previous ICU admission in last 6 months	MPM-0
History of angina	TIMI risk score
History of being hurt in a fall in the last year	Mayo Ambulatory Geriatric Evaluation

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