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SMART on FHIR in spine: integrating clinical prediction models into electronic health records for precision medicine at the point of care

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Abstract

Recent applications of artificial intelligence have shown great promise for improving the quality and efficiency of clinical care. Numerous clinical decision support tools exist in today's electronic health records (EHRs) such as medication dosing support, order facilitators (e.g., procedure specific order sets), and point of care alerts. However, less has been done to integrate artificial intelligence (AI)-enabled risk predictors into EHRs despite wide availability of validated risk prediction tools. An interoperability standard known as SMART on FHIR (Substitutable Medical Applications and Reusable Technologies on Fast Health Interoperability Resources) offers a promising path forward, enabling digital innovations to be seamlessly integrated with the EHR with regard to the user interface and patient data. For the next step in progress towards the goal of learning healthcare and informatics-enabled spine surgery, we propose the application of SMART on FHIR to integrate existing and new risk predictions tools in spine surgery through an EHR add-on-application

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Keywords

artificial intelligence; clinical decision support; diagnosis; electronic medical records; integration; machine learning; natural language processing; prediction; SMART on FHIR; spine

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Recent applications of artificial intelligence have shown great promise for improving the quality and efficiency of clinical care.[1, 2] For example, Lundberg et al. developed algorithms for prediction of intraoperative hypoxemia that performed better than anesthesiologists and subsequently improved anesthesiologist performance when made available with real-time model explanations.[3] Similarly, Hollon et al. developed algorithms for automated intraoperative tumor diagnosis that performed at the level of trained pathologists in a fraction of the time (150 seconds versus 20 minutes).[4] In spine surgery, applications of machine learning have included prediction and diagnosis in spinal oncology, trauma, infections, degenerative conditions, and adult spinal deformity.[5-19]

In 1928, L.J. Henderson reported the first medical use of a pictographic tool known as a nomogram.[20] A nomogram is a two-dimensional, graphical calculator. In the years following Henderson's report, nomograms were applied extensively for assisted clinical decision making.[21-27] In fact, nomograms and risk scores were ideal for clinicians when patient records existed on paper alone.

Today, after the 2009 Health Information Technology for Economic and Clinical Health (HITECH) Act, the majority of physicians in the United States use electronic health records (EHRs) for everyday clinical workflow.[28] EHRs bring a unique opportunity to integrate clinical decision support (CDS) tools into the clinical workflow. Numerous CDS tools exist in today's EHRs such as medication dosing support, order facilitators (e.g., procedure specific order sets), and point of care alerts.[29, 30] However, less has been done to integrate AI-enabled risk predictors into EHRs despite wide availability of validated risk prediction tools.[1]

Most risk prediction tools today exist as risk scores in published manuscripts or as web-or smartphone-based digital calculators by professional societies, academic medical centers, research study groups, or aggregating-platforms.[5, 6, 31] Clinicians that seek to use these systems at the point of care are often forced to interrupt their workflow, navigate to these separate systems, manually look-up and input the required patient information, wait for the results, and then return to their workflow in order to integrate the decision support guidance. In addition, the rise of EHRs has led to concerns of increased documentation time, impaired patient-physician interactions, and physician burnout.[29, 32-34] In order to realize the potential of AI-enabled risk prediction models, these models must be seamlessly integrated into EHRs such that they not only improve the performance of clinicians but also make the clinical workflow easier and more efficient.

An interoperability standard known as SMART on FHIR (Substitutable Medical Applications and Reusable Technologies on Fast Health Interoperability Resources) offers a promising path forward, enabling digital innovations to be seamlessly integrated with the EHR with regard to the user interface and patient data.[35-39] Prior work by two of the authors has shown that an EHR add-on-application for neonatology using SMART on FHIR resulted in time savings, high clinician usability ratings, and more clinically appropriate interventions.[35] This app also provided guidance on the likelihood of rebound hyperbilirubinemia following phototherapy.[40]

For the next step in progress towards the goal of learning healthcare and informatics-enabled spine surgery, we propose the application of SMART on FHIR to integrate existing and new risk predictions tools in spine surgery through an EHR add-on-application. We propose the following steps to accomplish this goal: (1) determination of the capacity for native EHR approaches to meet clinician needs, (2) selection of algorithms for prediction in spine surgery with demonstrated evidence of generalizability on external validation, (3) automating collection of real-time data required for model prediction using FHIR data interfaces, (4) development of visualization interfaces to allow for individual patient-level predictions and model explanations, (5) pilot studies to assess the impact of a SMART on FHIR EHR add-on-application on structure, process and patient outcomes, (6) deployment of the add-on-application at multiple institutions, (7) and prospective multi-center trials to determine the impact of the add-on-applications on time savings, user satisfaction, clinician performance, and patient outcomes.

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