Variance Reduction in Neurosurgical Practice: The Case for Analytics-Driven Decision Support in the Era of Big Data

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■ OBJECTIVE: **Variance between providers in neurosurgery can lead to inefficiencies and poor patient outcomes. Evidence-based guidelines (EBGs) have been developed; however, they have not been well implemented into the clinician workflow. Therefore, clinicians have been left to make decisions with incomplete information. Equally underused are the electronic health records (EHRs), which house enormous amounts of health data, but the power of that "big data" has failed to be capitalized on.**

■ METHODS: **Early attempts at EBGs were rigid and nonadaptive; however, with the current advances in data informatics and machine learning algorithms, it is now possible to integrate "big data" and rapid data processing into clinical decision support tools. We have presented an overview of the background of EHRs and EBGs in neurosurgery and explored the possibility of integrating them to reduce unwanted variance.**

■ RESULTS: **As we strive toward variance reduction in healthcare, the integration of "big data" and EBGs for decision-making will be key. We have proposed that EHRs are an ideal platform for integrating EBGs into the clinician workflow and have presented as an example of a successful early generation model, Neurocore. With this approach, it will be possible to build EBGs into the EHR software, to continuously update and optimize EBGs according to the flow of patient data into the EHR, and to present data-driven clinical decision support at the point of care.**

■ CONCLUSIONS: **Variance reduction in neurosurgery through the integration of evidence-based decision support in EHRs will lead to improved patient safety, a reduction in medical errors, maximization of the use of the available data, and enhanced decision-making power for clinicians.**

INTRODUCTION

The Institute of Medicine's landmark report, *To Err is Human: Building a Safer Health System*, brought into focus the preventable medical errors that have been negatively affecting patient outcomes.[1] Preventable medical errors in the neurosurgical field are of particular interest,[2-4] given the potentially fatal consequences.[5,6] Among the factors contributing to this issue is that variance between providers exposes the healthcare system to inefficiencies and worse health outcomes.[7-11] A need exists for the systematic accumulation of evidence to support clinical decision-making.[12] This decision support applies to both the medical management of neurosurgical patients, in particular, in the treatment of critically ill patients, and the indications for surgical interventions.

Neurosurgical evidence-based guidelines (EBGs) have been developed to address the problem of variance in neurosurgery.[13-15] In neurosurgery, EBGs have been met with scrutiny,[16] because

Key words
- Artificial intelligence
- Clinical decision support
- Electronic health records
- Machine learning
- Medical informatics
- Neurosurgery
- Variance reduction

Abbreviations and Acronyms
AI: Artificial intelligence
CDSS: Clinical decision support system
EBG: Evidence-based guideline
EHR: Electronic health record
HITECH: Health Information Technology for Economic and Clinical Health

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neurosurgery-specific EBGs are rare and have often been formulated without neurosurgeon input.[17] For the medical treatment of these patients, neurosurgery EBGs include management of ischemia and hemispheric stroke,[18-21] delirium,[22] traumatic brain injury,[23] and intracranial hemorrhage.[24,25] Regarding the indications for surgical interventions, EBGs have been created for deep brain stimulation for obsessive compulsive disorder[26] and surgery for low-grade glioma,[27,28] glioblastoma,[29] and brain metastases.[30] Multiple guidelines also exist in the area of spine surgery,[31,32] including the diagnosis and treatment of lumbar disc herniation,[33] isthmic spondylolisthesis,[34] and degenerative lumbar spondylolisthesis.[35]

However, the existing EBGs have not been efficiently and effectively implemented into the workflow of physicians[36,37] and, therefore, have been underused as decision support tools. In the current expansion of technology, the combination of "big data" and artificial intelligence[38-40] (AI) has created the opportunity to comprehensively integrate evidence-based decision-making into the healthcare system. These factors are converging during a time in which we have been seeing significant increases in electronic health record (EHR) adoption with the Health Information Technology for Economic and Clinical Health (HITECH) Act of 2009, from 3.2% among eligible hospitals before the HITECH Act to 14.2% after.[41] Given this healthcare and technology climate, we believe it is time to integrate EBGs with EHRs. This has the potential to bring enhanced decision-making support to physicians at the point of care, which could lead to improved patient safety and outcomes through variance reduction. In our own experience with creating an EHR specific to neurosurgery, which we have named Neurocore, we have found that the inclusion of these guidelines into the workflow has increased adherence, decreased variance, and improved patient outcomes.[42]

HISTORY OF INFORMATICS SYSTEMS

The use of computers as safety and research tools to monitor, record, and automate patient information was proposed as early as the 1960s.[43] In the proceeding decades, several attempts were made to integrate informatics systems into the medical system using clinical decision support systems (CDSSs).[44-47] In a systematic review of these systems, 4 features were identified as independent predictors of improved clinical practice.[48] All 4 of these features were also identified independently by other investigations: 1) automatic provision of decision support as a part of clinician workflow[49]; 2) provision of recommendations, rather than just assessments[50]; 3) usage of decision support at the time and location of decision-making[51]; and 4) computer-based decision support.[52] As processor speed and the availability of "big data" in healthcare have increased,[53] we have entered an era of immense possibilities, in which CDSSs can be more robust in their algorithms,[54] more adaptable to new data,[55,56] more seamlessly incorporated into existing technologies,[19] and more effective at improving patient outcomes.[57]

NEUROSURGERY INFORMATICS SYSTEMS

Monitoring and improving quality in neurosurgery is a complex and evolving task,[58] which could benefit from the power of neurosurgery-specific informatics systems. The National Neurosurgery Quality and Outcomes Database and NeuroPoint Alliance coordinates the prospective acquisition and distribution of nationally accrued neurosurgical registry data but does not systematically integrate it into an interactive informatics system.[59] A few attempts have been made at building integrated and interactive neuroinformatics systems. One is a problem-oriented relational database built for a neurosurgery department in Milan, Italy.[60] In San Francisco, California, a neuroinformatics system was developed for epilepsy patients to facilitate data storage and processing for research inquiries.[61] In Seoul, Korea, a system was designed specifically for in-clinic monitoring and data management for patients receiving deep brain stimulation for their movement disorders.[62] In Pavia, Italy, a workflow management system was integrated into the electronic clinical records for an epilepsy clinic.[63] Despite their somewhat limited scope and integration, these neurosurgery informatics systems have demonstrated the power and potential of applying "big data" in neurosurgical practice. In our own institution, we have been incorporating patient physiologic data with multiple data streams from the EHR into evidence-based machine learning algorithms for the treatment of critically ill patients in the intensive care unit setting.

SHORTCOMINGS OF, AND OPPORTUNITIES FOR, EBGs

EBGs are an early-phase model of a CDSS. Although they can aid physicians by presenting scientifically based evidence for the decision-making process,[12,16] EBGs have limited supporting data,[13,64] limited application for multimorbidity patients,[65] and limited generalizability and must rely on expert opinions when data are lacking. EBGs are rigid in their structure and stagnant in their incorporation of data,[66] and they have not been systematically adopted by healthcare providers.[67] Only when someone has manually reevaluated the data and redrawn the flowchart will clinicians receive an updated set of recommendations for diagnosing, treating, and managing a disorder. Thus, although EBGs have great potential to enhance the practice of neurosurgery,[68] they have failed to have a meaningful effect on clinician decision-making and patient outcomes. Our experience with Neurocore has allowed us to begin solving these issues.[42]

Current AI and machine learning applications present an opportunity to improve on that early EBG model.[69] By incorporating larger data sets and making many more connections than a human researcher is capable of in a fraction of the time, AI algorithms are able to leverage big data. Furthermore, with an AI algorithm, it is possible for an EBG to be continuously updated as new data are prospectively generated. Thus, it could be possible to leverage the power of big data to cover topics that previously unaided by EBGs. A deep learning neural network can be programmed to continually process clinical data, make meaningful connections, and then iterate and strengthen the algorithm.[38] This model would be constantly and automatically improving, without any manual human input and, as such, would provide physicians with the most well-informed and updated decision support tool. Using this approach, it would be possible to provide recommendations for patients with complex conditions and rare disorders, which are common to neurosurgical practice. With this data-driven technology, physicians would be informed with the most data- and evidence-based decision support to empower them to provide their patients with the best care. This has been the central goal with all our work in the area of machine learning algorithms—to incorporate these data seamlessly into the patient care work flow.

SHORTCOMINGS OF EHRs

From the introduction of computers in doctors' offices to the adoption of comprehensive hospital-scale electronic medical systems, the evolution of medical informatics has equipped clinicians with an advanced technology toolkit.[70] EHRs have been integrated into many healthcare facilities across the United States. They vary in their structure and content but most often include demographic data, medical history, presenting clinical symptoms, daily recording, tests and procedures performed, diagnoses, medications, physician and nurse assessments, clinical care plans, and discharge and referrals.[71]

Steven Stack, the former President of the American Medical Association, recently wrote "As physicians, we had hoped that these [EHR] tools would help facilitate patient engagement, reduce administrative burdens and promote the exchange of data. Those three things have definitely not happened. Instead, we're dealing with systems that won't talk to one another, cost too much to maintain and require us to spend an inordinate amount of time entering data instead of helping patients."[72]Although EHRs were heralded as the most important development in the healthcare technology revolution, with promises of improved documentation quality, increased administrative efficiency, superior patient safety, and better coordination of care,[73-75] these software applications have not resulted in the meaningful advances in patient care that were initially expected[76,77] and have actually transitioned to primarily being billing systems.[78,79] To meet the documentation requirements of the Centers for Medicare and Medicaid, such as a complete review of systems and a detailed family history, EHRs have been designed such that that they are not optimized to patient care.[80] In essence, EHRs have become digitized paper records without enhancing workflow, improving patient outcomes, or harnessing the potential of the big data they contain.[81]

INTEGRATION OF EBGs INTO EHRs FOR VARIANCE REDUCTION

In current EHRs, the restricted functionality of these advanced IT systems remains a difficulty for envisioning the improvements associated with the introduction of robust medical record systems.[82-84] The HITECH Act of 2009 and the Affordable Care Act of 2010 have accelerated the adoption of advanced information technology in healthcare settings, the development of emerging standards for interoperability, and the need for new data management capacity.[85,86] These efforts sought to bring greater evidence to clinical practice. However, to achieve this goal, it will be necessary to incorporate "big data" with EBGs into the workflow of clinicians. We envision this integration occurring within the EHRs because EHRs house a wealth of patient data and are at the interface of clinical care. The main areas for improvement that this integration will provide include enhanced patient safety by limiting both medical and processing errors, delivery of decision support, improved education and research, superior system management, and prospectively acquired data that can inform clinical practice.[73,87]

NEUROCORE

As we have previously discussed, we have jointly created a neurosurgery-specific EHR software program called Neurocore between the neurosurgery departments of Brigham & Women's Hospital and Memorial Hermann Hospital. Neurocore is a system designed to integrate EBGs into the clinical workflow.[42] This system is currently in use across a 12-hospital neurosurgery system in Houston, Texas.

During the course of an inpatient stay, the clinical team records information, collects vital signs, and records encounter notes into the EHR interface of Neurocore. The software has EBG algorithms programmed, which then analyze the patient data that are continually collected and stored. The physician is then presented with a clinical care suggestion at the point of decision-making and prompted on how to proceed according to the enhanced EBG algorithm. The physician is free to override the suggestion but must provide a reason for the override. Such data are also collected and implemented into future EBG iterations. By inviting the physician to consider the scientifically based approach at the point of care, the EHR promotes adherence to the most proven approach and reduces variance among providers, without disrupting the clinical team's workflow. It has been proved to provide an efficient and welcome addition by the clinicians, and the software has objectively led to fewer medical errors and better patient outcomes.[42]

With Neurocore as an example, EHRs have the potential to incorporate big data, AI algorithms, EBGs, and CDSSs to standardize clinical decision-making and aid physicians. This principle can be extended to all neurosurgery programs and to all hospitals, if EHRs are properly equipped to maximize this potential. The safe and effective integration of this data-driven clinical-decision software will rely on several best practice measures. The raw data will need to be processed and validated within its context. Analysis of the acquired data will need to be performed in reference to established benchmarks through the definition of clear metrics such as guideline structure based on peer-reviewed analyses[45,57] and recommendations of national healthcare authorities.[88,89] In addition, the data must be delivered to physicians using a method that aids in their decision-making, rather than detracting or distracting from it. By incorporating these elements of best practice, an EHR that integrates EBGs could lead to improved patient outcomes and safety, greater quality care, and cost-savings to healthcare facilities.

Neurocore represents an example of an EHR with a CDSS that was implemented before the HITECH Act and that has continued to be used and iterated in the post-HITECH period. It, therefore, represents an example of how a such a system can change and adapt during this period of rapid healthcare technology advancement. Thus, it serves as an interesting case study of how an EHR with an integrated CDSS can be used by a neurosurgical team. However, Neurocore is an early example of this type of solution. It is not the ultimate solution to neurosurgical EHR and CDSS needs but represents an encouraging start. Also, our experience with Neurocore should help inform future EHR innovations.

STUDY LIMITATIONS

The present report had some limitations. First, we focused on a retrospective review of our experience using a single neurosurgery EHR at a single institution. Future studies reporting on the comparative effectiveness of different EHRs at multiple institutions will be an interesting and important expansion on the successes we have reported. Nevertheless, we have seen in our experience that the integration of a CDSS into a neurosurgery-specific EHR is feasible and useful for variance reduction. These results are encouraging for the pursuit of future healthcare technology opportunities.

Furthermore, inherent limitations were present in the utility of the technology. Without the appropriate context and validation, the use of technology can be more distracting than helpful. We have seen this with the current and previous iterations of EHRs. To avoid this pitfall as we move forward with the opportunities of leveraging AI in our EHRs, it is of the utmost importance that clinicians who know and work in these systems be involved in the process. AI cannot solve all problems and certainly cannot do so all at once. However, when applied carefully and methodically to a series of specifically defined problems, the use of AI can be transformative. That is where the role of clinicians is key, both in defining the problems and crafting AI solutions. It will also be critical to use existing guidelines in the application of any of these solutions because they represent our gathered experience and knowledge over time. These systems can produce statistically valuable evidence that is absolutely clinically meaningless. Thus, all implementations of any AI system should include this realization, and these new evidence-based hypotheses must be verified and validated before integration into any clinical decision support system.

CONCLUSION

Variance between providers is a source of error and inefficiency in healthcare. As we strive toward variance reduction, the integration of big data and EBGs for decision-making will be a key factor. Early attempts at EBGs were rigid and not adaptive; however, with the advances in data informatics and AI algorithms, it is now possible to integrate big data and rapid data processing into clinical decision support tools. The most efficient method for integrating evidence-based decision support tools into the clinician's workflow is through EHRs. Thus, the most useful advance that could be made to EHRs would be the inclusion of EBGs for clinician decision support.

Overall, EHRs have been underusing the big data they house and have failed to capitalize on the opportunity to integrate EBGs into the clinician workflow. The advent of big data and analytics have provided us with the opportunity to change this and allow us to harness the potential of EHRs. In so doing, this vision of the healthcare future will provide better tools and more information to the clinician to aid in decision-making, enhancing the inherent satisfaction derived by clinicians in providing the best care possible.

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