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INTRODUCTION

Predictive analytics in medicine

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The annual healthcare spending in the United States reached a total of \$3.3 trillion or \$10,348 per person in 2016, an increase of 4.3% from the year before.[3] The growth rate at present is unsustainable and warrants a systematic re-evaluation of the healthcare model. According to the analysis presented by the National Academy of Medicine (formerly known as the Institute of Medicine), almost 30% of annual healthcare spending goes to procedures and therapies that are cost-ineffective.[6] In the current era of big data, large multicenter registries and administrative databases have become an effective tool for identifying optimum care models and for refining surgical and medical therapies to maximize efficacy and success.[4] One such database in the realm of neurosurgery is the Quality Outcomes Database, a national, multi-institutional, prospective registry that reports clinical and patient-reported outcomes.[1]

One of the core principles behind the utility of such registries is the use registry data in combination with predictive analytics to provide insights necessary to advance patient-focused, value-based care. Applications of predictive analytics consistent with those objectives include evidence-based, informed decision making; prevention of ineffective care; continuous quality improvement; and development of at-risk reimbursement models.

Traditional predictive modeling using techniques such as multivariate logistic regression have allowed us to advance our understanding of likely care outcomes and have been a mainstay of clinical data analysis for decades. Traditional predictive modeling, however, is significantly restricted by a set of assumptions that may not apply to real-world situations and may also be influenced by modeler bias, both of which do not apply to an emerging set of analysis techniques referred to as machine learning (ML).[8]

In this issue of *Neurosurgical Focus*, we profile a variety of traditional and novel predictive modeling techniques, the latter primarily focused on ML. ML, a vital branch of artificial intelligence, has recently been increasingly employed in the world of clinical research.[7] Very briefly, ML entails the use of computer algorithms to learn from "experience" or iterations of the data that are provided.[2,5] There are several practical and theoretical advantages of ML, a subfield of computer science, over traditional statistical modeling, a subfield of mathematics (many of which are discussed in the accompanying articles). ML for analysis of massive amounts of data is becoming increasingly prevalent in identifying "best" models of care. Therefore, it is likely that such methods will become a cornerstone in our collective efforts to more effectively and objectively increase the "value" of healthcare.

It is essential that neurosurgeons gain at least a basic understanding of the capability of advanced predictive analytics in medicine in order to more meaningfully participate in the cooperative evolution to a value-based healthcare system. We trust you will find the analyses provided here useful in that regard.

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Disclosures

Dr. Devin reports being a consultant for Stryker Spine and Wright Medical. He has received clinical or research support from Stryker Spine and he has been a defense expert witness for Medtronic.

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