Disclosure Information: Dr Dexter reports to the Division of Management Consulting of the University of Iowa's Department of Anesthesia which provides consultations to corporations, hospitals, and individuals. This includes the topic of case duration prediction, as in the current letter. Dr Dexter receives no funds personally other than his salary and allowable expense reimbursements from the University of Iowa and has tenure with no incentive program. He and his family have no financial holdings in any company related to his work, other than indirectly through mutual funds for retirement. Income from the Division's consulting work is used to fund Division research.

Accurately Predicting Case-Time Duration

In reply to Dexter and Epstein

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We thank Drs Dexter and Epstein for their response to our article titled, "Improving operating room efficiency: a machine learning approach to predict case-time duration."[1] We appreciate and recognize their numerous contributions to the literature on applying Bayesian methods to predict case duration. However, we would encourage the authors to have a more nuanced dialogue on how our different approaches, methods, and results can enhance operating room management—rather than a broad criticism.

Drs Dexter and Epstein criticize the novelty of our scope, approach, and practicality. Simply put: their previous work seeks to adjust surgeon estimates; our methods involve the prediction of case-time estimates completely independent of surgeon input. Philosophically, these are divergent ideas: if the case-time duration can be accurately predicted, as per our approach, we can rely less on the surgeon-as-an-estimator and more on the integration of robust data to improve models. Given the current advances in data accessibility and management, our approach is especially timely and applicable to any operating room.

We will address their criticisms in 3 points. First, we use a more comprehensive dataset as compared with their studies. A key aspect is that we included a variety of preoperative patient factors into our model to account for what Dexter and Epstein have termed "process variability."[2,3] While Dexter and Epstein cite previous studies using larger case volumes, the data available in their studies included only the procedure type, surgeon, and case-time, without considering patient data. Further, they considered it a limitation that we restricted our cases to only those performed in the operating rooms (ie not in the radiology or cardiology suites) and weekday cases (ie not after-hour or emergency cases). The exclusion of these cases was deliberate and was designed with an operating room manager in mind. In fact, their work seems to have taken the same approach.[3] Therefore, we defend our claim of using a novel dataset and scope.

Second, we applied multiple, modern machine learning algorithms to predict case duration and selected the best performing algorithm to build our final set of models. On the contrary, Dexter and Epstein have applied a Bayesian method to estimate case time durations. Traditional statistical methods are unable to derive patterns from large datasets. Dr Dexter's website bibliography lists 2 other papers that have used approaches similar to ours, both of which were published recently and neither of which included case volumes that approached that of our dataset.[4-6] Therefore, we defend our statement that ours was a novel approach.

Third, we have kept a keen focus throughout our work on implementation. We acknowledge that our machine learning models did not include predictions for longest expected time, anticipated gaps, or expected time remaining. However, these are certainly achievable with a machine learning approach combined with a robust dataset. We believe that our approach serves a different objective than that of Drs Dexter and Epstein. Our goal was to accurately predict case-time durations based on preoperative patient procedure and personnel data to optimize surgical scheduling. For that reason, and unlike several previous studies, we excluded any procedural data that were exclusively available intraoperatively or postoperatively, such as CPT codes. We designed both service-specific models and surgeon-specific models to generate predictions that govern the majority of cases in a hospital. We have already begun piloting a tool to improve the case-time estimates at our institution that relies both on accurate and appropriate data collection and on the machine learning models to interpret those data.

We intend for this work to be an early stepping-stone to realizing the dual potential of modern electronic medical records and modern "big data" computational tools in order to better use operating room and the nurses, doctors, and technicians who work within them.

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Clarifying the Role of Targeted Muscle Reinnervation in Amputation Management

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Valerio and colleagues[1] described using targeted muscle reinnervation (TMR) as an adjunct to major limb amputations. In this study, TMR was found to decrease pain in the residual limbs compared with a recruited control group. The study has 2 significant problems.

First, the study population and the control group included a variety of upper and lower limb amputations, with no clear description of the surgical techniques used. For the control group (which was recruited from clinics, support groups, conferences, and advertisements), it would be important to know details of the patients' operations and whether patients with complications were more likely to respond to the investigators' outreach than patients without complications.

Next, the authors did not fully consider the available knowledge regarding the connection of proximal sensory nerves to distal motor nerves. Chang and colleagues[2] and Goldberg and colleagues[3] used sensory-to-motor nerve connections to provide sensation to microsurgical muscle flaps transplanted to weight bearing recipient sites. Sensation was achieved in most of these patients, presumably through reinnervation of the substantial numbers of sensory fibers in "pure" motor nerves.

Experimental studies of sensory-to-motor reinnervation of denervated muscle have demonstrated clear advancement of the proximal sensory nerves into various terminations, including muscle fibers and free nerve endings. Sensory-to-motor reinnervation, however, resulted in significant muscle atrophy. Sensory reinnervated muscles lost 62% of bulk by weight.[4] Although such a loss of muscle mass could be a positive outcome for flaps used in foot and ankle reconstruction, similar loss of bulk could substantially change the contour of an amputation stump, complicating prosthesis management over time.

The study by Valerio and colleagues, therefore, includes a poorly defined control and ignores an important physiologic consequence of sensory-to-motor reinnervation of muscles, specifically, muscle atrophy.

The proper control group for the authors' strategy is simple implantation of significant sensory nerves into local muscles. This long-established, technically simple procedure can significantly reduce pain in up to 96% of patients undergoing initial neuroma surgery, aborts neuroma formation experimentally, and does not cause muscle atrophy.[5,6] A prospective study of similar amputation groups who receive either nerve transposition or TMR would truly clarify the role of TMR in amputation management.

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