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Modeling Learning in Surgical Practice

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OBJECTIVE: Methods that model surgical learning curves are frequently descriptive and lack the mathematical rigor required to extract robust, meaningful, and quantitative information. We aimed to formulate a method to model learning that is tailored to dealing with the high variability seen in surgical data and can readily extract important quantitative information such as learning rate, length of learning, and learnt level of performance.

METHODS: We developed a method where progressively more complex models are fitted to learning data. These include novel models that split the learning data into 2 linear phases and fit adjoining lines using least squares regression. The models were compared and the least complex model was selected unless a more complex one was significantly better. Significance was tested by Fischer tests. We applied this method to total hip and knee replacements using imageless navigation, analyzing the operative time for a surgeon's first 50 and 60 operations, respectively. This method was then tested against 4 sets of simulated learning data.

RESULTS: The proposed method of progressive model complexity successfully modeled the learning curve among real operative data. It was also effective in deducing the underlying trends in simulated scenarios, created to represent typical situations that can practically arise in any learning process.

CONCLUSIONS: The novel modeling method can be used to extract meaningful and quantitative information from learning data displaying high variability seen in surgical practice. By using simple and intuitive models, the method is accessible to researchers and educators without the need for specialist statistical knowledge. (J Surg Ed ■:■■■-■■■.

KEY WORDS: medical education, learning curve, surgical learning, learning model

COMPETENCIES: Practice based learning and improvement

INTRODUCTION

Learning curves graphically represent the relationship between learning effort and learning outcome. The concept of a learning curve was first introduced to predict aircraft manufacturing costs in 1936,[1] but in the past 2 decades, it has been increasingly adopted in surgical practice.[2–5] It was recognized that surgeons operating at the early stages of their learning curve pose a potential hazard, and modeling learning has since received considerable attention.[6,7] Any new procedure will require a period of learning, and training schemes seek to ensure that trainees achieve a satisfactory standard of performance.[8] Understanding the learning curve is useful in comparing new procedures to the current standard of care, ensuring that surgeons included in randomized trials are at similar stages in their learning.[9] Multilevel data modeling is becoming increasingly common in many disciplines including medical education, and simplicity in modeling methods is of paramount importance to widen the application of such analytical techniques.[10]

Anatomy of a Learning Curve

The *y*-axis of a learning curve represents an outcome of learning, often called the performance index. Although

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patient outcomes (e.g., survival and quality of life scores) are preferred as they are perceived to more accurately represent the end-goal of an operation, *process* outcomes (e.g., operative time and blood loss) are more often used owing to their accessibility. The *x*-axis of a learning curve represents the learning effort, usually made up of sequential attempts at a procedure. The learning curve is merely a graphical representation of the association between the 2 variables.

The concept of learning, plateau, and unlearning are descriptions of trends in the evolution of the performance index with increasing learning effort. Learning is defined as an improvement in the performance index with time (e.g., decrease in operative time), whereas unlearning is the opposite. A plateau is defined as a steady state represented by a constant value of the performance index and usually represents an expert performance level that shows no signs of further improvement.

Learning Curve Modeling

The stereotypical learning curve shows a negative exponential relationship that is based on the theory of deliberate practice,[11,12] where the rate of learning progressively slows as an individual gains experience, culminating into an asymptote or plateau. Learning a procedure depends on numerous variables, rendering it difficult to agree on an accepted model to fit all learning curves. Surgical learning data are riddled with variability from patient, surgeon, and procedure-specific factors, making learning curve modeling particularly troublesome. Systematic reviews have concluded that statistical methods used to analyze surgical learning curves have been mainly descriptive and unhelpful in determining learning parameters.[13,14] Cook et al[15] characterized 3 key parameters of a learning curve: the initial level of performance, the rate of learning, and the level of the expert plateau. Papachristofi et al[9] identified the importance of the duration of the learning period and used a 2-phase model to help estimate this. These key parameters of a learning curve are integral to meaningful, quantitative interpretation of data in the various applications of learning curve analytics.

Current Approaches to Modeling Surgical Learning

The first question that needs to be addressed in any attempt to model learning is whether the data display learning, and if so, whether the learning later converges to a plateau. Often, but not always, this can be answered by merely looking at a scatter diagram of a learning data. However, this method is both subjective and qualitative, and is rendered near-useless when data exhibit high variability, obscuring the underlying trends.

A very popular method includes chronologically dividing cases into consecutive groups and comparing groups with *t*-tests. However, the determination of group size is arbitrary and may hinder interpretation of the learning curve.[5] For example, if a plateau has been reached in the fifth operation, and grouping has occurred in sets of 50, the effect of learning will likely be dwarfed when comparing this group to the subsequent one.

Although it makes intuitive sense that an exponentially decaying function underlies a typical learning curve, fitting such higher-order functions to learning data yields little information in terms of the sought after learning parameters. Fitting higher-order functions to surgical learning makes even less sense, where high uncertainty underlies the data owing to intraoperator and interoperator variability.

A line followed by a plateau, as used by Papachristofi et al,[9] identifies the need to model learning by intuitively simple models that extract key learning parameters from the data, but it does not accommodate for a multitude of learning scenarios.

Key limitations of current models which we seek to address are as follows:

(1) These methods attempt to fit a specific learning model to data without assessing whether a different model may fit better.

(2) The mathematical calculations required to both fit the model as well as extract the key learning parameters are often not amenable to an analyst who is not trained in advanced mathematics.

(3) No research to date has sought to propose a model general enough to accommodate for the multitude of scenarios that arise in surgical practice.

We aim to describe a simple, novel method to model all learning curves in the context of high variability seen in surgical practice. The key characteristics of a learning curve should be readily identifiable regardless of the anatomy of the curve, the mathematical prowess of the analyst, and the variability of the data.

METHODS

Our senior consultant surgeon, competent at hip and knee arthroplasty, had not previously used imageless navigation. We, retrospectively, collected data from his first 60 navigated total knee replacements and first 50 navigated total hip replacements. The time to complete each operation was sourced from operative records, defined as time from "knife-to-skin" to "skin closure." We apply a novel method to model operative time (*y*-axis) as a function of the ordinal number of operation (*x*-axis) for these, and other simulated sets of learning data.