date of discharge, sex, and center were used to link the 2 databases, whereby a proportion of 87.4% of exact matches was seen with the lowest unmatched cohort accounting in the lower surgical risk categories.

Experienced researchers can, with careful design and sophisticated statistical methodology, develop models based on administrative data for certain conditions that may be appropriate for profiling. Zafar and colleagues⁴ have gone one better with their linking methodology, which could allow researchers to capitalize on the strengths of both databases and expand the pool of data available for analysis. Furthermore, this novel algorithm may provide metrics of performance that are not accurately analyzed and/or presented by either of the databases in isolation. However, it must be tested and validated in a multi-institutional fashion and expanded to identify the vast majority, if not all, of the cardiac procedures within congenital heart surgery. Otherwise, this algorithm could end up like Goldilocks, in the classic children's book,⁸ as she runs into the forest, never to be seen again.

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Commentary: What's in a name? The effect of misclassification in administrative data in the setting of congenital heart disease surgery

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When William Shakespeare wrote "What's in a name? That which we call a rose by any other name would smell as sweet,"¹ I believe he intended to say that names in of themselves don't have meaning or add value to the subject being named. However, I would contend that in our field of surgery on congenital heart disease (CHD), there is value in a name if it is self-descriptive and universally accepted.

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CENTRAL MESSAGE

Misclassification, one thorn in the side of administrative database research.

When it comes to disease nomenclature and procedure classifications in CHD, administrative data sources and clinical data sources use different nomenclature. Diagnoses and diagnostic complexes are not only classified using different terms, but the terms themselves are often not directly translatable and may differ in text, number, and

hierarchy. The problem is farther amplified in procedure coding. There is inherent complexity associated with surgical interventions for CHD. This complexity may be summarized in a simple name like the “Norwood operation” or may have to be spelled out to different components like arch repair, atrial septectomy, and systemic to pulmonary shunt, with the assumed Damus Kay Stansel anastomosis, which may not have a code in the nomenclature being used altogether. Giving a disease entity or an intervention a name that is incorrect is misclassification.

From a statistical perspective, misclassification can be differential (DM) or nondifferential (NDM). In DM, a disease entity or intervention (or any other thing) tends to be wrongly classified as a certain other classification within the available set of classes. In contrast, NDM is random. A disease or intervention is misclassified to another random classification in the available set of classes. NDM is similar to measurement error in that it is random, and it may be corrected for by statistical methods that report conclusions with a certain confidence interval to account for the level of random error. If one was able to measure or estimate the degree of NDM, there are methods to account for the added random error in the reported estimates. Simple bias analysis, probabilistic bias analysis, Bayesian bias analysis, modified mixed likelihood, multiple imputation for measurement error, regression calibration, and propensity score calibrations are some of the methods that may be useful to deal with NDM. These methods are outlined with some statistical coding examples in a nice overview by Funk and Landi.²

When dealing with DM, all bets are off. The magnitude and direction of error are not random and therefore no statistical wizardry is going to inform the misinformed. Unfortunately, in the field of CHD, it is entirely reasonable to assume that most misclassification will be DM. A certain disease or intervention tends to be misclassified as a certain other not as a random class. These misclassifications are sometimes institutional, group, or even individual coder tendencies.

In this issue of the *Journal*, Zafar and colleagues³ have rigorously studied an administrative dataset from Pediatric Health Information System database. They developed a complex mapping algorithm to find corresponding codes (classes) for the Society of Thoracic Surgeons-Congenital Heart Surgery Database for 10 so-called benchmark operations from the *International Classification of Diseases, 10th Revision*, codes used in the Pediatric Health Information

System database. They found the overall sensitivity to be 91% and specificity to be 99%. Sensitivity was greater for 4 of the 10 benchmark operations compared with the remaining 6 operations. They concluded that the mapping algorithm generated may facilitate population-based research using administrative data.

There are several contentions that should come to mind. First, this analysis was limited to 10 common and clearly defined (at least by the Society of Thoracic Surgeons-Congenital Heart Surgery Database codes) benchmark procedures, and even in those benchmark procedures the sensitivity of the mapping algorithm dropped to less than 91% in 6 of the 10 procedures. It is very likely that the accuracy of the mapping, measured as sensitivity and specificity, would be lower for more complex and less frequent procedures. Second, the misclassification is most probably DM; therefore, it is not correctable by larger data or complex statistics. Large data only make systemic errors larger and may hide the error with very small confidence intervals and tiny *P* values. Lastly, the jump from analytical research and hypothesis generation or even testing to health administration and making decision about resource allocation or program performance and quality of care would be an unjustified leap of faith based on fallacy.

There is light at the end of the tunnel, however. Thanks to a substantial effort by a large group of CHD health practitioners, the forthcoming *International Classification of Diseases, 11th Revision* has largely adopted the International Paediatric and Congenital Cardiac Code used in clinical databases.⁴ When that is realized, and the administrative databases are populated with the new codes, we will hopefully see the difference a name can make.

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