Ever since Deyo et al. translated the Charlson Comorbidity Index from chart-abstracted information into International Classification of Diseases, Ninth Revision diagnosis codes, the repurposing of administrative billing data has been a staple of health services research and epidemiological surveillance. This is especially true for studies of rare but devastating outcomes, such as mortality and morbidity among neonates with very low birth weight, in which the collection of clinical data across multiple hospitals is an expensive undertaking. In a study in this issue of Pediatrics, Tawfik et al makes an important contribution to this research by validating the codes used in administrative data against information extracted from medical charts from a large number of hospitals across California. They find excellent correlation for important variables that researchers rely on for surveillance and performance modeling, and they find some areas for improvement. In general, clinicians can feel confident that the big issues affecting neonatal outcomes, such as very low birth weight, cesarean delivery, and maternal hypertension, are coded with high accuracy on administrative records, whereas codes for rare or subjective conditions are less accurately coded.

They also find that the correlation between clinical and billing data did not vary substantially by hospital. This is a significant finding because researchers using administrative data have shown that where a mother receives care has a significant bearing on her and her infant’s outcomes. By comparing risk-adjusted outcomes derived from administrative data across hospitals, we can identify low-performing hospitals and take steps to improve the quality of care at these hospitals. Doing so not only reduces adverse outcomes overall, but, because poor-performing hospitals tend to treat a high proportion of mothers who are minorities, it also reduces the racial and ethnic disparities in neonatal outcomes. Clearly, this effort would be hindered if differences in coding practices by hospital made the identification of low-performing hospitals error prone.

The Tawfik et al. study has limitations that argue for further research on the utility of administrative data, at least in the near term. Neither set of data used in the study captures key elements of labor and delivery care that we know are important for improving outcomes outside the NICU, such as induction, cervical dilation on admission, and length of first stage of labor. Authors of future studies should also consider assessing the validity of billing records for conditions that are known to differ substantially by mother’s race, contribute to adverse perinatal outcomes, and are generally measured poorly in administrative data. Among these conditions are maternal obesity, hypertension, and bleeding complications. Finally, the interpretation of positive predictive value and negative predictive value...
in the Tawfik et al study should be made with caution. Both of these measures are sensitive to the prevalence of the underlying condition or procedure, which are elevated in a NICU population.

Tawfik et al argue for a greater effort to improve coding on administrative databases on the grounds that this would be less costly and therefore more feasible for most institutions than developing a purpose-built system for extracting the information. However, this is clearly a second-best solution; if data are important for clinical care, they are important to collect on their own and not just for billing. In the long-term, we need to stop relying on administrative data and focus our efforts on the much richer data available in electronic health records (EHRs). Authors of recent studies suggest that advances in machine learning and natural language processing might obviate many of the costs associated with data abstraction. Rajkomar et al applied machine-learning techniques to EHR data that included providers’ orders, diagnoses, procedures, medications, laboratory values, and clinician notes. These data were read directly from the EHR, without any processing of the data into a curated set of variables, as typically precedes traditional statistical analyses.

Rajkomar et al made 2 important findings. First, using a deep learning algorithm but no human input, they could predict the diagnoses on the discharge abstracts from EHR data with a high degree of accuracy, thus obviating human coders entirely. Second, they could predict outcomes such as in-hospital death and excess length of stay with greater accuracy than traditional models that relied on preprocessing of curated variables. These breakthroughs suggest that we may soon stop relying on repurposed financial data to study society’s most important health outcomes.

**ABBREVIATION**

EHR: electronic health record

**REFERENCES**


Repurposing of Administrative Data for Research: Still Useful but for How Much Longer?
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The online version of this article, along with updated information and services, is located on the World Wide Web at:
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