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Accuracy of surveillance for surgical site infection after spine surgery: a Bayesian latent class analysis using four independent data sources

VANCOUVER SPINE SURGERY INSTITUTE
Specialized care for the spine and spinal cord

Oliver Lasry, MDCM, MSc, FRCSC and John Street MD, PhD, FRCSI

Division of Spine Surgery, University of British Columbia, Vancouver Spine Surgery Institute

Background

Surgical site infections (SSIs) are morbid and costly complications of spine surgery. Understanding the impact that interventions have on reducing SSI risk requires appropriate surveillance.[1-3] Unfortunately, valid approaches to conducting SSI surveillance in spine surgery patients are lacking because of varying SSI case definitions, the lack of a gold-standard definition for SSIs, and the elevated costs related to conducting resource-intensive monitoring of this complication. As such, there is a need to develop methods that allow stakeholders in spine surgery to accurately conduct SSI surveillance using resource-friendly and readily-available data sources. Thereafter, the allocation of resources to the valid evaluation of interventions that mitigate the risk of SSIs will be possible.

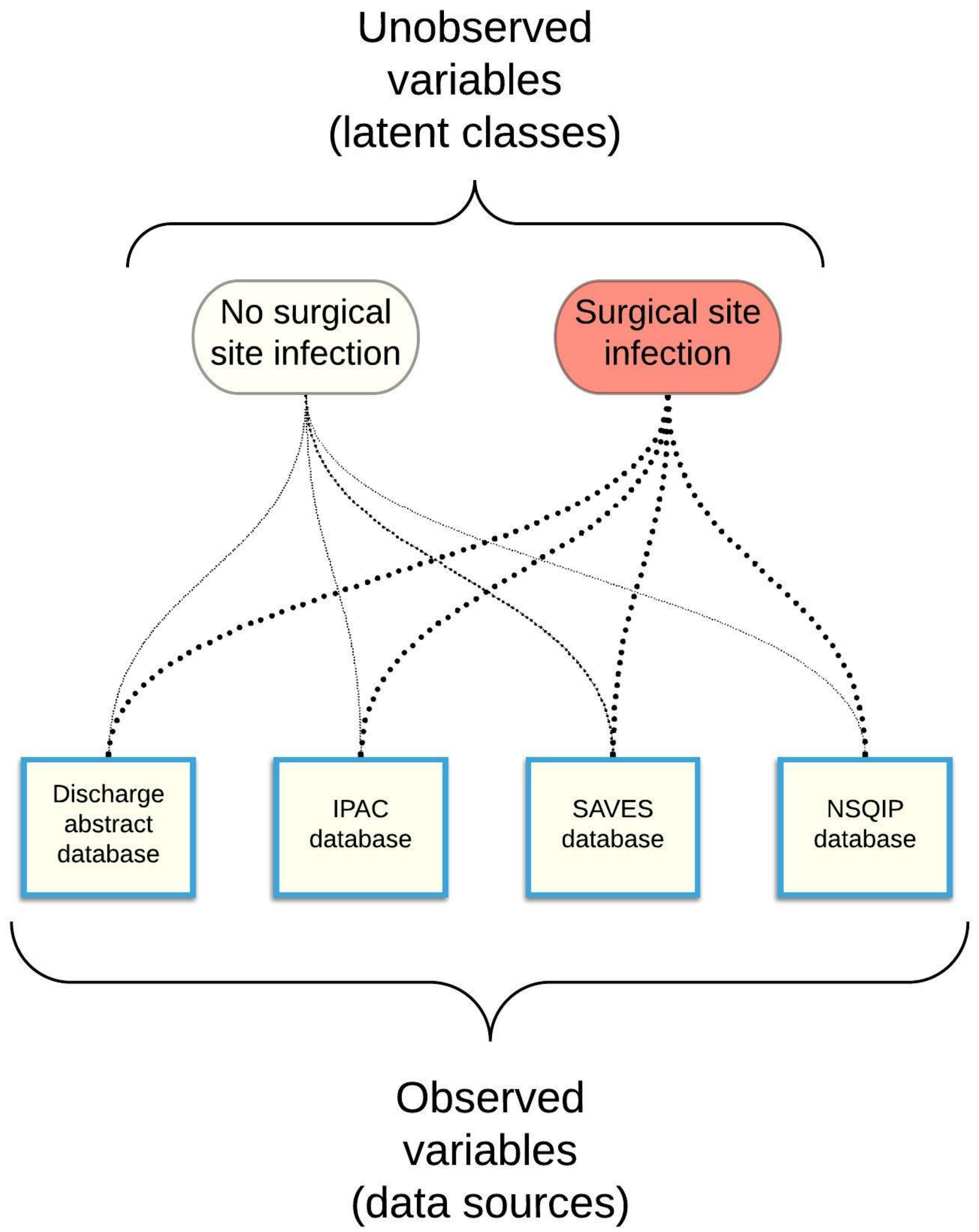
Objectives

We aimed to assess the accuracy of 4 data sources that capture SSIs after spine surgery while estimating a measurement error-adjusted SSI incidence, without relying on a gold-standard definition for SSI, which does not exist.

Methods

We assessed the accuracy of SSI surveillance algorithms across the following 4 independent data sources for patients undergoing spine surgery at the Vancouver General Hospital in 2017: 1) the discharge abstract database (DAD) using International Classification of Disease (ICD) codes, 2) the National Surgical Quality Improvement Program (NSQIP) database, 3) the Infection Prevention and Control Canada (IPAC) database, and 4) the local Spine Adverse Events Severity (SAVES) database.[1,2,4,5] A Bayesian latent class model was used to assess the *sensitivity* and *specificity* of each data source to identify SSI and to estimate a measurement-error adjusted *incidence*, without relying on a gold-standard SSI definition.[6] The positive predictive values and negative predictive values of each data source to detect SSIs was also assessed using simple arithmetic calculations with the incidence, sensitivity, and specificity measures that were estimated.

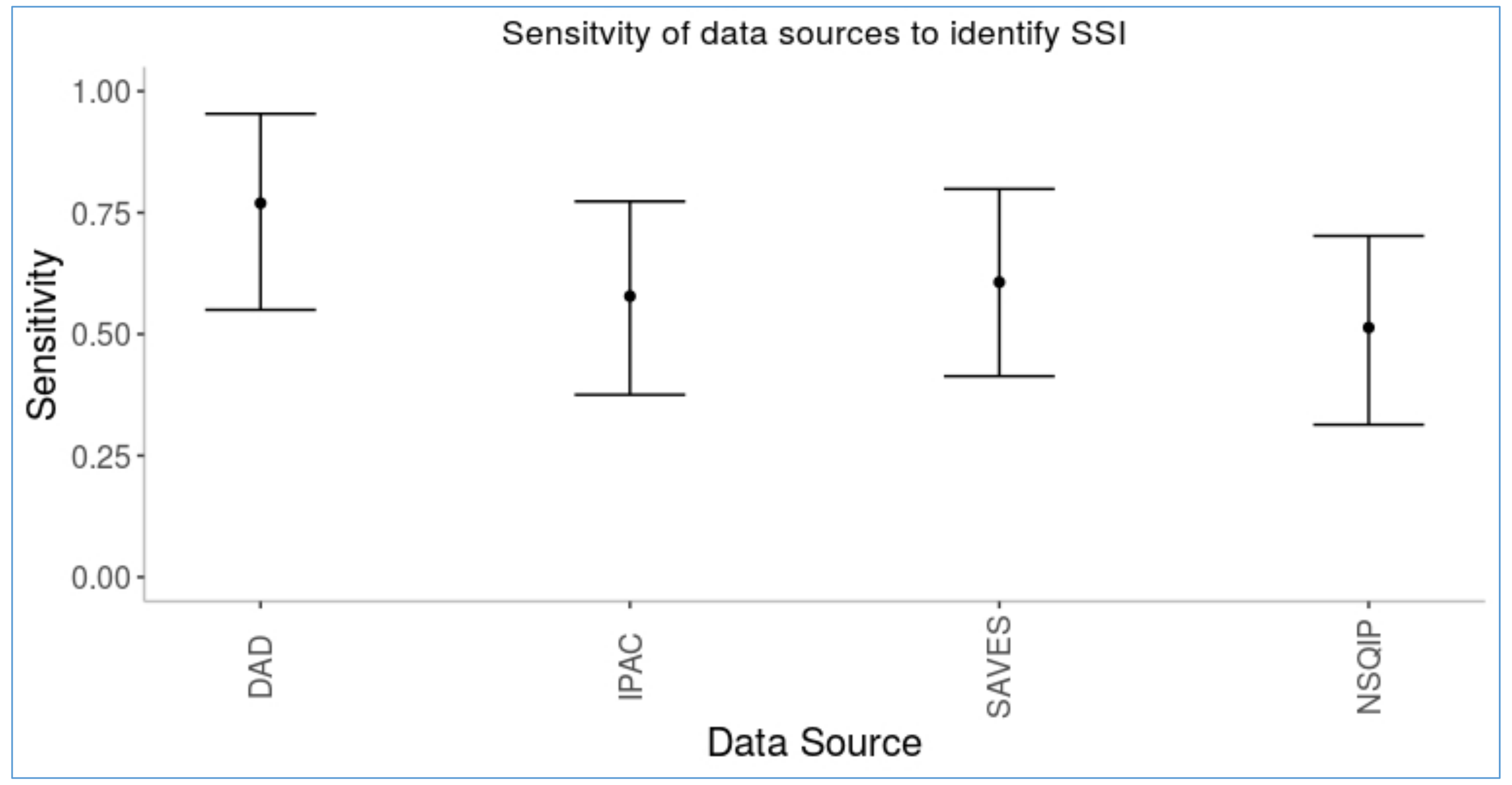
Heuristic model of latent class analysis

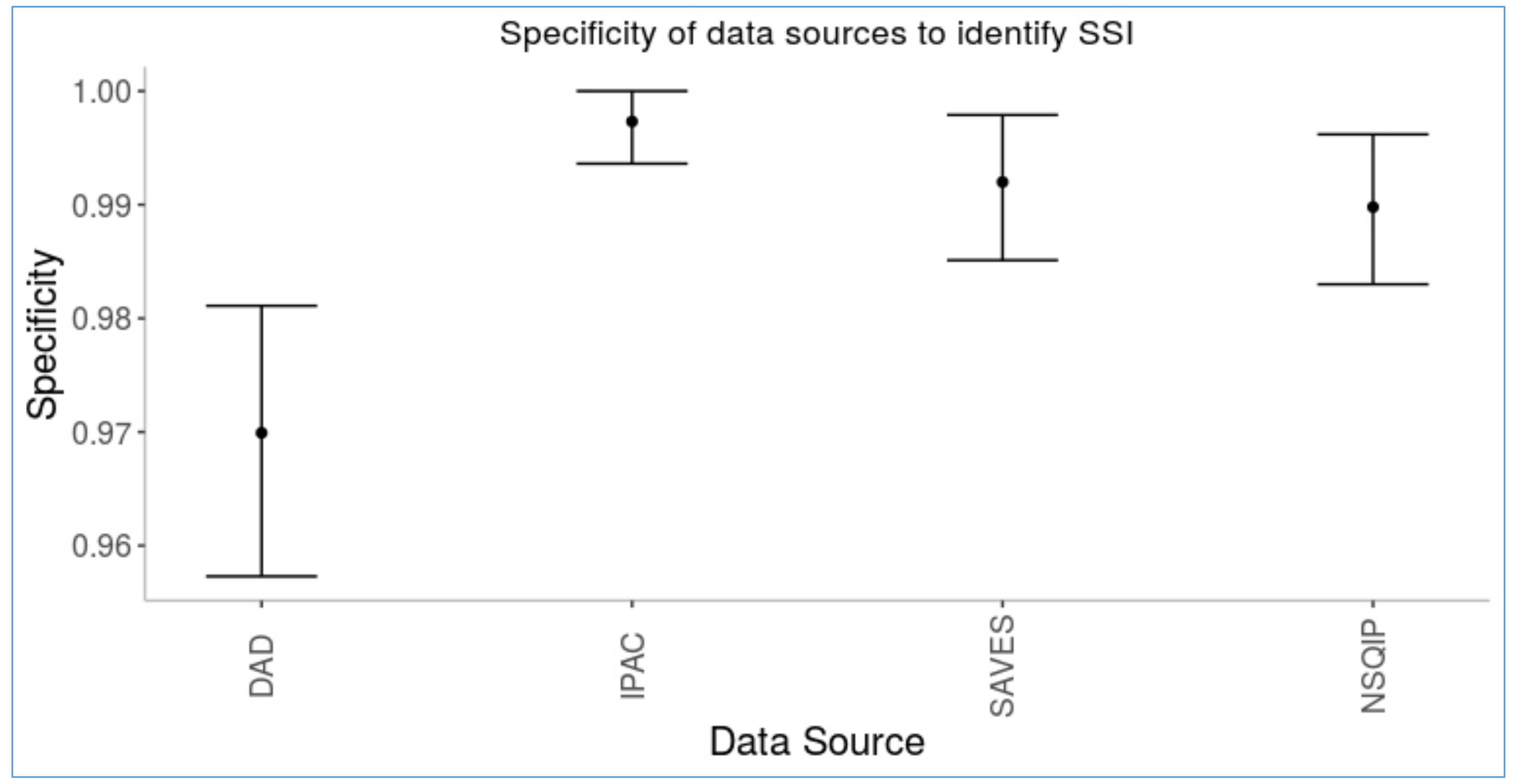


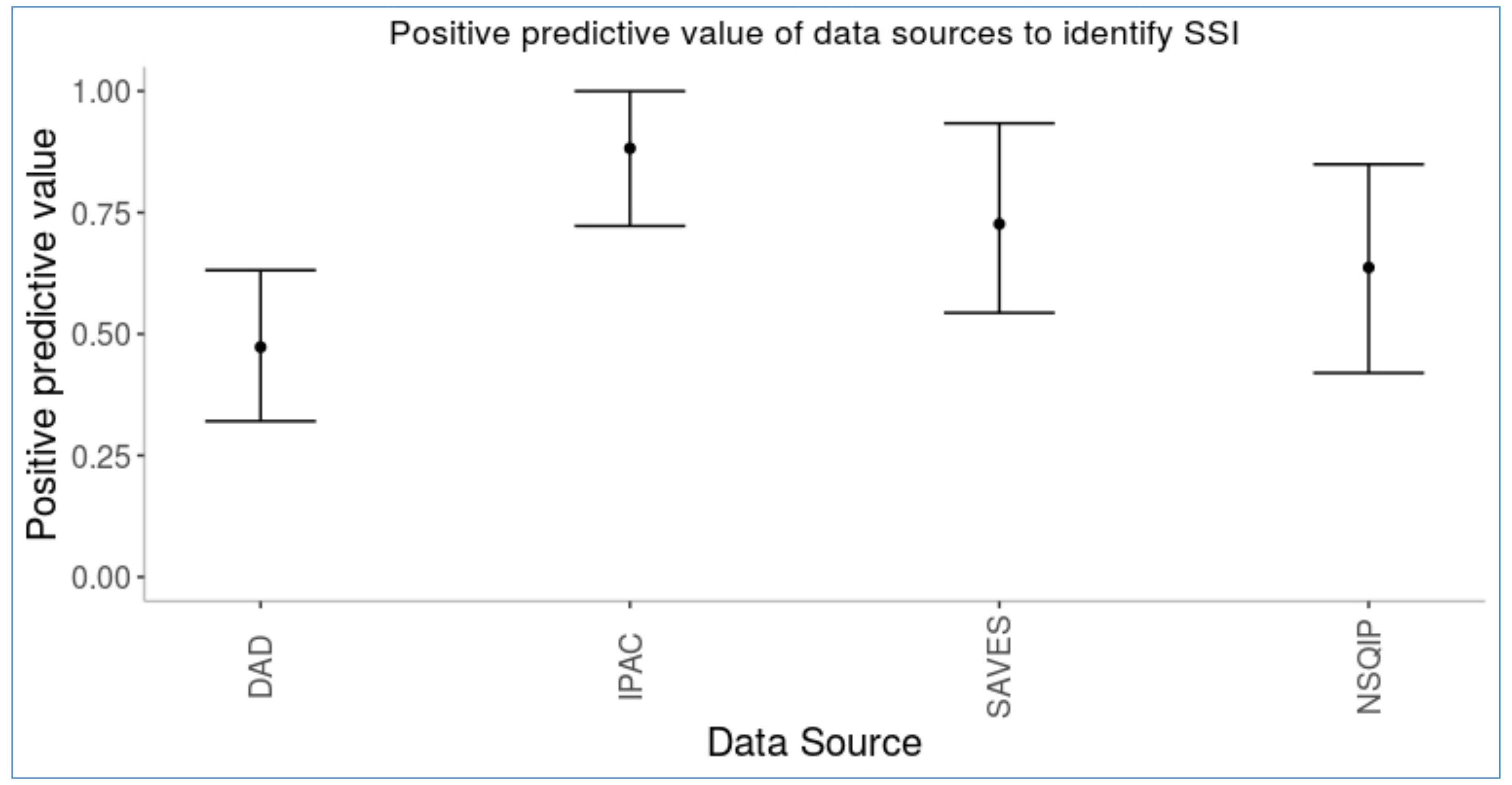
The 2-class latent class analysis uses the observed data to classify patients in 1 of 2 disease states, either with a SSI or without a SSI. Patients can meet the case definition of a SSI in 0 to 4 of the data sources. The patterns of case definition responses across the population allows the latent class model to classify patients in the appropriate "unobserved" latent class. The model estimates the probability of an individual being positive/negative to a case definition/data source given that they have a SSI/no SSI, also known as the sensitivity/specificity of that data source. In this Bayesian model, prior information was not necessary as the model converged with the supplied data across the 4 data sources. The correlation between data sources was assessed to ensure appropriate model fit.

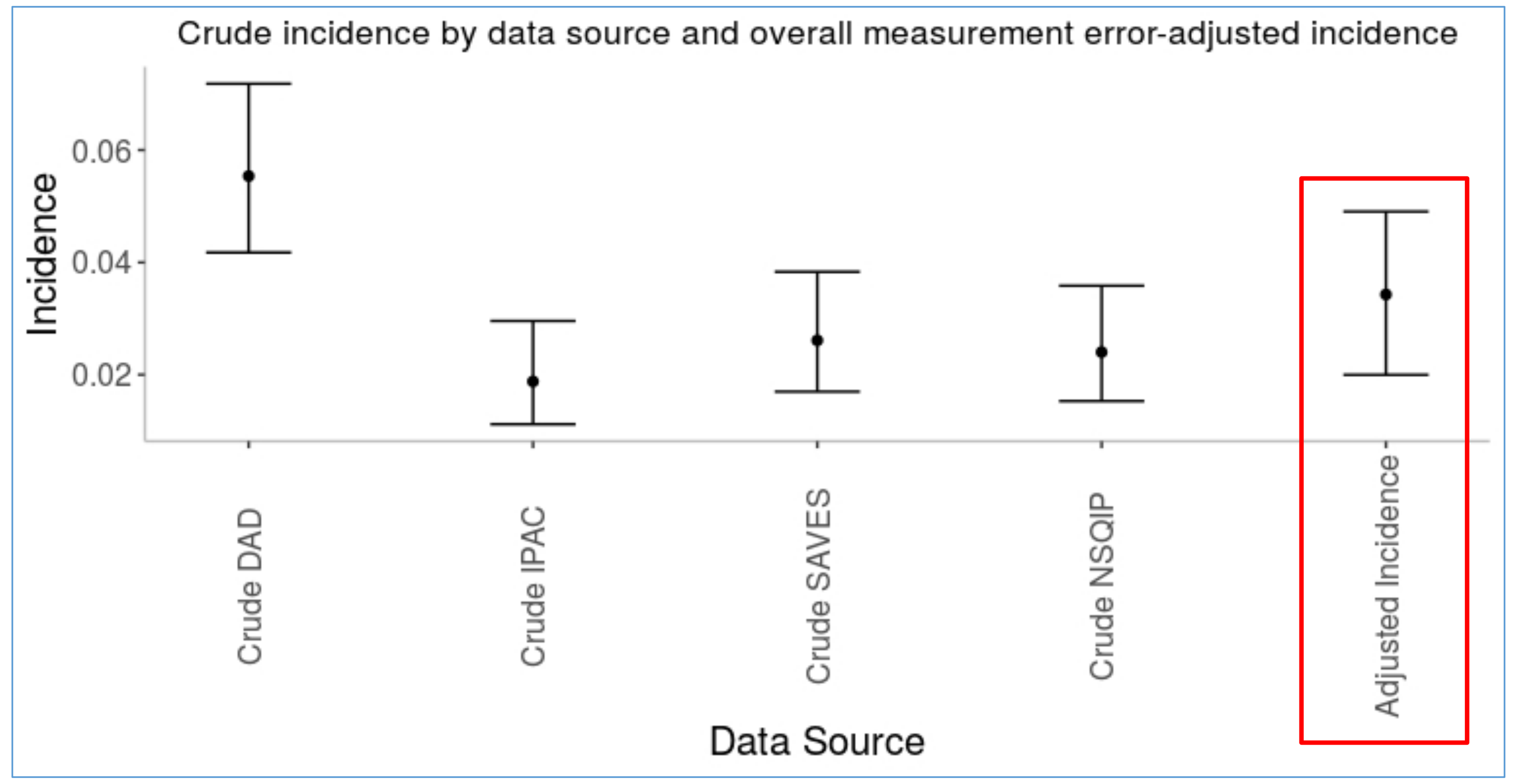
Results

A total of *976 patients* underwent spine surgery in 2017. The most sensitive data source was the DAD (0.77, 95% CrI 0.54,0.95), while the least sensitive was the NSQIP database (0.51, 95% CrI 0.32,0.71). The most specific data source was the IPAC database (0.997, 95% CrI 0.993,1.000), while the least specific was the DAD (0.970, 95% CrI 0.957,0.981). The measurement error-adjusted SSI incidence was 0.034 (95% CrI 0.021,0.051). The DAD overestimated the incidence, while the other data sources underestimated the incidence.









Conclusions

SSI surveillance in the spine surgery population is feasible using several data sources, provided that measurement error is accounted for. Stakeholders in spine surgery SSI surveillance should use data sources readily accessible to them, such that the SSI burden and the impact of interventions to reduce it are properly assessed in a timely and resource-friendly fashion. Using the information from this analysis, high-quality epidemiological studies evaluating interventions that mitigate SSI will finally be possible.

References

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