

doi: 10.1111/1753-6405.12985

## Sepsis in cancer: a question of definition

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We commend te Marvelde et al. for evaluating sepsis in Victorian cancer patients through linkage of population-based datasets and state registry data.<sup>1</sup> Using administrative coding data (ICD-10-AM) to define sepsis, sepsis incidence for the period 2008-2015 was estimated to be 6,200 sepsis events per 100,000 cancer patients in Victoria. We advocate the use of linked data to evaluate health services delivery and infection epidemiology in oncology, acknowledging that valuable primary datasets have not generally been utilised for this purpose, and recognising the unmet need to date for reliable and automated methods of monitoring infections in high-risk cancer populations.

However, careful interpretation of findings is required given the limitations of ICD-10 for case-ascertainment. Previous studies have demonstrated that ICD coding consistently underestimates the rate of sepsis, with sensitivity spanning 52% to 74%.<sup>2,3</sup> As such, some have argued that ICD-9 and ICD-10 data are unsatisfactory for estimating the burden

of severe sepsis when used in isolation.<sup>4</sup>

The Peter MacCallum Cancer Centre whole of hospital sepsis pathway implementation demonstrated that up to one-third of patients were missed by coding alone,<sup>3</sup> and that other clinical data such as antimicrobial approvals and pathway documentation was required to identify true cases.<sup>5</sup>

Multiple ICD-10 abstractions have been used in an attempt to more reliably define sepsis and severe sepsis, including implicit, explicit and clinical coding. Explicit coding includes microbiology sepsis codes ± clinical sepsis R codes, whereas implicit coding includes infection codes ± organ dysfunction codes.<sup>6</sup> To date, however, considerable discordance has been identified in sepsis rates calculated using both implicit and explicit coding methods compared to rates defined using clinical criteria (Table 1).<sup>7</sup> In particular, the explicit coding strategy used in te Marvelde et al.<sup>1</sup> has been demonstrated to have lower sensitivity for severe sepsis detection when compared to implicit coding<sup>6</sup> (Table 1).

There is a need for reliable monitoring of sepsis in cancer patients, given the requirements for evaluation of quality improvement activities within healthcare, such as implementation of bundles of care to reduce sepsis burden and mortality.<sup>5</sup> Looking ahead, validation of administratively coded data must be performed using gold-standard clinical data. If validity is demonstrated, we propose that a nationally-agreed definition for sepsis be supported through engagement of key stakeholders, including clinicians and staff responsible for clinical coding.

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**Table 1: Published performance metrics of different coding abstractions for severe sepsis.**

Study	ICD-10 abstraction	Sensitivity (95% CI)	Specificity (95% CI)	Positive predictive value (95% CI)	Negative predictive value (95% CI)
Fleischmann-Struzek et al. (2018) <sup>6</sup>	Clinical	25.1% (16.0–34.6)	99.6% (99.1–100)	56.1%	98.5%
	Explicit	41.9% (30.9–51.9)	99.4% (99.8–99.9)	59.6%	98.8%
	Implicit	59.0% (48.1–69.1)	95.7% (94.4–97.1)	22.1%	99.1%
Rhee et al. (2015) <sup>8</sup>	Explicit	60.3% (55.5–64.9)	–	–	–
	Implicit	72.1% (67.6–76.2)	–	–	–
Bouza et al. (2016) <sup>9</sup>	Explicit	62.2%	–	–	–
Iwashyna et al. (2014) <sup>10</sup>	Implicit	50.4% (14.8–85.7)	96.3% (92.4–100)	70.7% (51.2–90.5)	91.5% (79.0–100)
Whittaker et al. (2013) <sup>11</sup>	Explicit	20.5% (18.6–22.4)	–	–	–
	Implicit	47.2% (44.8–49.5)	–	–	–

Notes:

CI, confidence interval;

ICD-10, *International Statistical Classification of Diseases and Related Health Problems, Tenth Revision*

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