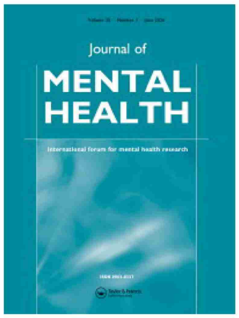

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EDITORIAL

Reducing incidents of self-harm in mental health wards: a tale of two rates

Self-harm is the most common patient safety incident reported in the National Health Service (NHS) mental health services (Quinlivan et al., 2020). A recent study (Ndebele et al., 2024) reported that the use of a surveillance technology, Oxevision, helped reduce inpatient incidents of self-harm in a mental health NHS Trust. Oxevision uses infra-red sensitive cameras in people's bedrooms to help staff visually confirm a person is safe, measuring vital signs, without disturbing them (https://www.rethink.org/news-and-stories/media-centre/2023/11/our-position-on-oxevision-the-new-monitoring-system-in-mental-health-units/). This has been introduced in approximately half of NHS mental health Trusts in England (Buckley et al., 2024). As the use of such surveillance technology is not without concern (Griffiths et al., 2024), it is worth knowing how much reduction in self-harm incidents they actually bring.

Ndebele et al. (2024) observed that, in intervention wards with Oxevision, the rate of self-harm per month in 2018 and 2019 fell from 8.89 to 6.94 incidents per 1000 occupied bed days respectively. Table 1 shows what these rates mean in terms of actual number of incidents per month, assuming full occupancy (i.e., if every bed is occupied by someone for 30 days). In a ward with 20 beds (ward A), this means a reduction from five to four incidents per month (5.33 to 4.16). In a slightly larger ward with 22 beds (ward B), this means a reduction from six to five incidents per month (5.87 to 4.58). After the installation of Oxevision, these wards observed a reduction of about one incident per month. From an expected annual total of approximately 64–70 incidents depending on ward size, we now anticipate 50–55 incidents (i.e., up to 22% improvement).

While 22% is a notable reduction, it was reported in Ndebele et al. (2024) that Oxevision brought about a "44% relative percentage change" in reduction of self-harm incidents. The latter clearly suggests a much bigger improvement. So, let's take a closer look at how they arrive at this estimate. Ndebele et al. (2024) first showed that monthly incident rates for the intervention ward (A) were 0.78 times lower than the previous year (6.94 in 2019 vs 8.89 in 2018). This ratio for the non-intervention ward (C) showed that monthly incident rates were 1.39 times higher than the previous year (12.63 in 2019 vs 9.07 in 2018). The 'relative change' ratios in ward A and C (0.78 vs 1.39) now give a new ratio of 0.56. The amount of change observed in the ward A was 0.56 times smaller than the amount of change observed in ward C. For simplicity of presentation, they reversed the direction ($1 - 0.56 = 0.44$), and converted it into a percentage (i.e., multiplying by 100), giving a "44% relative percentage change".

The 44% is calculated by taking a ratio of two ratios. Just because we have a "ratio" for reduction and increase does not mean the ratio between them makes sense. Consider the illusion created when looking out of a train window: a nearby train travelling in the opposite direction makes our own train appear to move faster than it really is. In the same way, comparing a reduction in ward A (0.78) with an increase in ward C (1.39) exaggerates the apparent effect. The two directions of change are not directly comparable and doing so risks overstating the benefits of Oxevision.

In defence of Ndebele et al. (2024), they have carefully selected the intervention and non-intervention wards based on "similarity of the patient cohort, ward size and clinical ways of working". However, the rise in self-harm incidents in the non-intervention ward, from 65 to 91 (ward C), warrants careful consideration. It is important to acknowledge that the study was explicitly framed as a mixed-methods before-and-after evaluation. Such designs are common and often appropriate in settings where randomisation is not feasible. Nevertheless, these designs are prone to confounding and uncontrolled between-group differences, meaning that comparative rate ratios of this form must be interpreted cautiously.

Without comparing the wards for now, we showed there was a reduction from previous year of about one incident per month in the intervention ward. This brings us to the second issue. Absolute rate changes provide a more tractable account than relative rate changes as the latter can be misleading (https://www.youtube.com/watch?v=ELNt0XZYsAQ). For instance, an improvement of 50% in relative terms may mean a reduction in the probability of an event from 2% to 1%. The former implies a large improvement. The latter puts the benefits in perspective by elucidating the actual change in absolute terms (from 2 out of 100 down to 1 out of 100 affected). This distinction may seem pedantic but has non-trivial implications for interpreting any relative comparison, whether of risks, rates, or counts.

Table 1. Stipulated number of self-harm incidents per month, assuming full occupancy, calculated from rates reported in Ndebele et al. (2024).

Ward	Number of beds	Bed days in a month (full occupancy)	Year	Rate*	Rate calculations	Number of incidents per month	Stipulated annual average
A	20	20 × 30 = 600	2018	8.89	(600 / 1000) x 8.89	5.33	64
			2019	6.94	(600 / 1000) x 6.94	4.16	50
B	22	22 × 30 = 660	2018	8.89	(660 / 1000) x 8.89	5.87	70
			2019	6.94	(660 / 1000) x 6.94	4.58	55
C	20	20 × 30 = 600	2018	9.07	(600 / 1000) x 9.07	5.44	65
			2019	12.63	(600 / 1000) x 12.63	7.58	91

*rate per 1000 bed days reported in Figure 1 of Ndebele et al. (2024).

When examining health economic impact of Oxevision for the NHS Trust, Buckley et al. (2024) calculated cost savings of £118,762 per year based on a 44% reduction in inpatient incidents of self-harm. The premise of this statement assumes a reduction in absolute incident counts. It implies that from an annual average of 64, we now anticipate 36 incidents. But as shown in Table 1 (ward A), it should be 22% improvement (from 64 to 50). The cost savings as such are likely to be lower if Buckley et al. (2024) had not misinterpreted the relative rate changes reported in Ndebele et al. (2024) as a reduction in absolute incident counts.

The above scenario could have been averted if time series plot of monthly incident rates were used instead of annual averages. This is elegantly illustrated in Perla et al. (2011) with the use of time series plots, or run charts, a commonly used analytic method in healthcare improvement. Even though a simple comparison of two annual averages shows an apparent improvement that attains statistical significance (Figure 2 in Perla et al., 2011), the visual displays over time in run charts, aided by rules with minimal mathematical complexity, can reveal a starkly different story (e.g., an initial improvement that did not last).

The use of time series plots would also create opportunities for interrupted time series modelling (Fretheim & Tomic, 2015). This is potentially well-suited to the scenario in Ndebele et al. (2024), where randomisation is not possible (Hategeka et al., 2020; Kontopantelis et al., 2015). The benefit of surveillance technology, like Oxevision, is currently still an issue of active debate (Griffiths et al., 2024). As pointed out by an anonymous reviewer, access to methodological expertise varies widely among those working to improve healthcare. To help NHS deliver safer, higher-quality and more efficient care, study findings should be reported in a manner that is proportionate to the strength of the underlying evidence.

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