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Changes in Healthcare-Associated *Staphylococcus aureus* Bloodstream Infections after the Introduction of a National Hand Hygiene Initiative

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Background. Interventions that prevent healthcare-associated infection should lead to fewer deaths and shorter hospital stays. Cleaning hands (with soap or alcohol) is an effective way to prevent the transmission of organisms, but rates of compliance with hand hygiene are sometimes disappointingly low. The National Hand Hygiene Initiative in Australia aimed to improve hand hygiene compliance among healthcare workers, with the goal of reducing rates of healthcare-associated infection.

Methods. We examined whether the introduction of the National Hand Hygiene Initiative was associated with a change in infection rates. Monthly infection rates for healthcare-associated *Staphylococcus aureus* bloodstream infections were examined in 38 Australian hospitals across 6 states. We used Poisson regression and examined 12 possible patterns of change, with the best fitting pattern chosen using the Akaike information criterion. Monthly bed-days were included to control for increased hospital use over time.

Results. The National Hand Hygiene Initiative was associated with a reduction in infection rates in 4 of the 6 states studied. Two states showed an immediate reduction in rates of 17% and 28%, 2 states showed a linear decrease in rates of 8% and 11% per year, and 2 showed no change in infection rates.

Conclusions. The intervention was associated with reduced infection rates in most states. The failure in 2 states may have been because those states already had effective initiatives before the national initiative’s introduction or because infection rates were already low and could not be further reduced.

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Healthcare-associated infections increase the risk of death and cause longer stays in the hospital. Infections can be avoided by breaking the cycle of the transmission of microorganisms from healthcare workers, patients, and the environment. A key strategy for breaking this cycle is hand hygiene, but the success of hand hygiene depends on high rates of compliance among hospital staff, and compliance rates have been below 50% in some areas. Recent initiatives have been successful in increasing hand hygiene compliance. Two studies also showed a reduction in hospital-acquired infections, although another observational study found no association between increased hand hygiene compliance and decreased infection rates. A Cochrane review on strategies to improve hand hygiene compliance found just 4 eligible studies that had a randomized or quasi-randomized design and concluded that the current evidence was “insufficient” to draw a firm conclusion.

The Australian National Hand Hygiene Initiative (NHHI) aimed to develop a national approach to improving hand hygiene and monitoring its effectiveness (http://www.hha.org.au). The initiative was based on the World Health Organization’s “Clean care is safer care” campaign. The details of the initiative and theory behind its design are in the manual. The Australian initiative aimed to achieve sustained improvements in hand hygiene compliance by using ongoing education, regular hand hygiene compliance auditing using the “5 moments” program, and standardized assessment of *Staphylococcus aureus* bloodstream (SAB) infection rates. The aim was for every hospital in Australia to adopt the initiative. We tested the effectiveness of the Australian NHHI by ex-
examining whether it was associated with a reduction in SAB infection rates. We used an observational quasi-experimental design based on monthly SAB infection rates. We had usable data from 6 of the 8 states and territories, and we present separate results for each state and territory because of differences between the states with respect to preexisting hand hygiene practices.

METHODS

Our hypothesis was that the intervention changed the monthly rates of infection. We did not specify a direction for this change, so all hypotheses tests are 2-sided. The following analysis plan was developed a priori, and no post hoc tests were made. The plan was agreed upon at a meeting of the project steering group that involved the project’s chief investigators and representatives from every state and territory. The results were discussed with representatives from each jurisdictional health department before publication.

Data

Data on healthcare-associated SAB infections are routinely collected by Australian hospitals and are reported both to their state or territory health authority and nationally for performance monitoring. The hospitals chosen were the 5 largest public hospitals (by number of acute care beds) in New South Wales, Victoria, Queensland, Western Australia, and South Australia; the 3 largest public hospitals in Tasmania; and the single main public hospital in the Northern Territory and Australian Capital Territory. This gave 30 hospitals. We then selected the next-largest 20 public hospitals throughout Australia to give 50 hospitals in total. We requested all of the available monthly data for the 50 hospitals. Data on multiple infection types were available, but we only examine infections that are due to hospital-associated SAB infections in this analysis, because the steering group felt that this infection had the most consistent data collection protocol (including definitions). SAB infection was defined using the nationally agreed definition as endorsed by the Australian Commission on Safety and Quality in Healthcare. Both methicillin-resistant *S. aureus* and methicillin-susceptible *S. aureus* were included.

The dates of available data differed between states (Figure 1). All states and territories had data for the preintervention and postintervention periods except for the Northern Ter-
ratory, which provided no data, and Victoria, which provided data but with too many missing data to be usable. These 2 states were therefore excluded.

The NHHI was implemented at different times across the country. Because collection of auditing data formed the basis of the intervention, we used the first report of auditing data for each hospital as the start of the intervention.

The data used here were provided to us by individual hospitals (sometimes via the state bodies). We verified the data quality and checked the infection definitions used. The study was approved by the appropriate human research ethics committees in each state and territory, and the release of data was additionally approved through the research governance processes appropriate to each hospital. The study was also approved by the Queensland University of Technology human research ethics committee.

Study Design

We used a before-and-after quasi-experimental design by comparing the infection rates after the intervention with those before, while controlling for other potential changes over time (see below for details). Similar designs include an interrupted time series, change-point estimation, segmented regression, and stepped-wedge design.

We ran the analyses separately in each state, because the intervention was implemented on a state-by-state basis, with overall coordination at both a state and national level. There were also important differences between states in terms of average infection rates and preexisting hand hygiene campaigns and infection prevention policies. Hence, it was thought likely that the effect of the intervention would vary by state.

Statistical Methods

We examined the change in infection rates after the intervention. Discussions with the project steering group led us to believe that the change in infection rates could have a number of different patterns. For example, the intervention may have gradually reduced rates from month to month in a linear way, or it may have caused an abrupt lowering in rates. There may have been a delay between the start of the intervention and its impact on rates because of learning time and the time taken for the intervention to reach all parts of the hospital. There may also have been a delayed increase in rates after the initial impact of intervention wore off. To capture these possibilities, we examined 12 possible changes over time (Figure 2). Models A and D adhere to the null hypothesis that the intervention had no impact on rates. Models K and L allow a potential delayed increase in rates once the intervention effect has worn off.

The regression model for the counts of infections in hospital \( i \) in month \( t \) was as follows:

\[
c_{i,t} \sim \text{Poisson} \left( \mu_{i,t} \right), \quad i = 1, \ldots, M, \quad t = 1, \ldots, n_i
\]

\[
\log(\mu_{i,t}) = \log(n_{i,t}/10,000) + \delta_{i} + \alpha_{t} + \text{change}_{c,\alpha}
\]

where \( M \) is the total number of hospitals and \( n_i \) is the number of months observed in hospital \( i \). A Poisson distribution is the most appropriate for modeling counts. The offset, \( \log(n_{i,t}) \), divides the mean counts, \( \mu_{i,t} \), by the denominator of bed days, \( n_{i,t} \), which we standardized to per 10,000 bed-days (Table 1). Including the bed-day denominator helped control for changes over time, such as long-term trends in increasing hospital use and seasonal changes in hospital admissions.

A change in denominator reporting over time could create a spurious change in infection rates. We asked the infection control practitioner in each hospital about any changes, and either none were reported or, where changes did occur, the data we received were retrospectively standardized. We plotted the denominators in each hospital over time to look for sudden changes that would indicate a change in denominator, and none were found.

We controlled for any seasonal patterns in infection rates using a categorical variable for month (\( \delta \)). We used a random intercept in each hospital (\( \alpha_{t} \)) to control for differences in the average infection rates between hospitals. We were not interested in differences in infection rates between hospitals but were instead interested in the within-hospital change due to the intervention and the average within-hospital change per state.

We examined a step-change due to the intervention (model A in Figure 2) by modeling the change in equation (1) as:

\[
\text{change}_{c,\alpha} = \begin{cases} 
0, & t < T_i \\
\beta, & t \geq T_i
\end{cases}
\]

where \( T_i \) is the time the intervention was introduced in hospital \( i \). This assumes that the rates changed immediately at the time of the intervention and remained consistently changed at all times thereafter.

In another model, we assumed a linear change due to the intervention (model C in Figure 2) using the following:

\[
\text{change}_{c,\alpha} = \begin{cases} 
0, & t < T_i \\
\beta \times (t - T_i), & t \geq T_i
\end{cases}
\]

We examined a possible delayed intervention effect (eg, model G in Figure 2). This is plausible because it may take time for the changes promoted by the intervention to become standard practice. We examined delays of 1–6 months from the start of the intervention.

We examined a second change some time after the intervention (eg, model L in Figure 2). This second change could happen if the impact of the intervention on staff behavior wanes with time. We assumed that this second change happened sometime between 2 and 12 months after the intervention.

We examined a linear change in rates before the intro-
duction of the intervention (eg, model F in Figure 2). This is important because, if rates were already decreasing, then the effect of the intervention is the additional change in rates after accounting for the previous linear decrease.

We selected the best model from the 12 using the Akaike information criterion (AIC). The AIC is a trade-off between model complexity and a good fit to the data. The equation for the AIC is minus twice the log-likelihood (goodness of fit) plus twice the number of parameters (model complexity). The smaller the AIC, the better the model, but a difference of 2 or less is not considered important. We used the following steps to choose the best model: (1) of the 12 models, find that with the lowest AIC (AICbest); (2) of the remaining 11 models, find that with the next lowest AIC (AICnext); (3) if AICnext − AICbest ≤ 2, then use the next model if the next model has fewer parameters (principle of parsimony). The order of model simplicity, as determined by the number of parameters, is {A} < {B, C, D, G} < {E, F, I, J} < {H, K, L}, where the subscripts are the number of parameters for modeling the change in infection rates. Therefore, model A is simpler than models B and C, and models B and C are equally complex (with 1 extra parameter). An example of the model selection process is shown in Figure 3. An advantage of using the AIC is that the best fitting model is chosen regardless of the statistical significance (or otherwise) of any change in infection rates. The AIC is a useful statistic for quantifying the evidence for a set of competing models, and it has been used in a wide variety of model selection problems, including choosing between competing sets of independent variables, prediction models, and covariance structures.

For the best model in each state, we estimated the per-

<table>
<thead>
<tr>
<th>State</th>
<th>Denominator</th>
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<tbody>
<tr>
<td>ACT</td>
<td>Occupied bed-days</td>
</tr>
<tr>
<td>Queensland</td>
<td>Inpatient-days</td>
</tr>
<tr>
<td>NSW</td>
<td>Bed-days</td>
</tr>
<tr>
<td>South Australia</td>
<td>Multiday and same-day bed-days, excluding psych bed-days</td>
</tr>
<tr>
<td>Tasmania</td>
<td>Patient care–days</td>
</tr>
<tr>
<td>Western Australia</td>
<td>Multiday and same-day bed-days</td>
</tr>
</tbody>
</table>

**NOTE:** ACT, Australian Capital Territory; NSW, New South Wales.
We obtained usable data for 38 of the 50 largest public hospitals in Australia. We had 2,304 months (192 years) of monthly infection rates across 38 hospitals in 6 states. The average number of months before the intervention was 29 per hospital, with an average postintervention time of 32 months.

The best fitting model in each state is shown in Figure 4. In ACT and Queensland, there was an immediate reduction in rates that was sustained over time (model B). In New South Wales and South Australia, there was a linear decrease in rates after the intervention (model C). In Western Australia, there was no change in rates (model A), and in Tasmania, rates decreased at the same rate before and after the intervention (model D).

The percentage reduction in rates in the ACT after the intervention was 28% (95% CI, 6%–45%; \( P = .017 \)). The reduction in rates in Queensland was 17% (95% CI, 6%–27%; \( P = .002 \)). The linear reduction in rates in New South Wales was 11% per year (95% CI, 7%–16%; \( P < .001 \)). The linear reduction in rates in South Australia was 8% per year (95% CI, 1%–15%; \( P = .019 \)).

For the 2 states where no change was detected, we considered the possibility of a false-negative error due to a lack of statistical power (Table 2). We examined the power for models B and C, because these were the best models in 4 states, and for percentage reductions in the range of those observed in 3 states where there was a statistically significant change. We had excellent statistical power for Tasmania; hence, the lack of observed change associated with the intervention is unlikely to be a false-negative error. The power for Western Australia was lower, and this was because the rates of infection were already relatively low in Western Australia. Finding a change in a rare event requires a larger sample than is required for a common event.

**Discussion**

We found reductions in hospital-associated SAB infection rates that were associated with the intervention in 4 of the 6 states, with no change in rates in 2 states (Figure 4). The reductions in rates in the 4 states were all statistically significant. In future work, we will examine whether these reductions are large enough to translate into a conclusion that the NHHI was cost-effective.

In Tasmania, rates were already decreasing before the intervention was introduced (Figure 4), and the intervention failed to immediately decrease rates. Tasmania was already on a successful trajectory, and it may have been wiser to wait to intervene until rates became flatter, because the existing hand hygiene programs were already achieving the desired reductions in infections. We recommend plotting average infection rates over time before introducing any intervention aimed at reducing infection rates to avoid introducing po-
tentially unnecessary interventions. However, it is possible that, without the introduction of the NHHI, the change in rates may have worsened. Therefore, the program may have been successful in maintaining a decreasing trajectory.

We used a statistical approach that examined a range of plausible patterns in infection rates, whereas previous studies have only examined a narrow range of possible patterns. One previous study used separate linear regressions before and after an intervention and then compared the 2 regression slopes. However, this ignores any change in the intercept (eg, model E in Figure 2) and will overestimate the effect of an effective intervention if the postintervention period has a positive intercept and underestimate it if it has a negative intercept. Another study (also examining the impact of the NHHI) assumed that the rates of infection were flat before the intervention (model G in Figure 2), but this will not give an accurate estimate of the intervention if rates were changing before the intervention (model F in Figure 2). If rates were already coming down before the intervention, then assuming that rates were flat will overestimate the effect of an effective intervention, whereas if rates were increasing before the intervention, then an effective intervention would be underestimated. We recommend trying a range of potential models when examining changes in infection rates over time, because using a narrow range of models can lead to false-positive or false-negative findings or biased estimates that under- or overestimate the intervention effect.

An interesting observation is that, in the 4 states where there was a reduction in rates, this reduction occurred immediately after the introduction of the initiative. Therefore, models B and C were always preferred to similar models with a delayed change, such as models G and J (Figure 2). The fast reaction to change may reflect the large change in practice with the initiative, including education and regular audits.

Our study design did not have any control hospitals that did not receive the intervention. This means that our study is vulnerable to time-dependent confounders, such as other changes to national, state, or hospital-level infection policy.

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**Figure 4.** Estimated mean change in infection rates after the intervention in each state or territory. Infection rates per 10,000 bed-days. Results from the best-fitting regression model in each state or territory; the letters in parentheses are the best model (see Figure 2). The dashed line is the time of intervention. ACT, Australian Capital Territory; NHHI, National Hand Hygiene Initiative; NSW, New South Wales; QLD, Queensland; SA, South Australia; Tas, Tasmania; WA, Western Australia.
that may have reduced infection rates. This potential confounding was somewhat reduced, because the intervention was introduced at multiple times, which decreases the overall correlation between the intervention and other changes. However, the timing of the intervention was not randomized by hospital. A randomized intervention time would have further reduced any correlation and therefore would have further reduced the potential bias of time-varying confounders.

Changes to infection control practice and policy occurred in most of the hospitals during the study period. The timing of these changes varied between hospitals, and via interviews with infection control staff, we found no evidence of these changes occurring concurrently with the introduction of the hand hygiene intervention. Overall, we believe that such potential changes are unlikely to confound the observed associations between the NHHII and monthly SAB infection rates.

The more proximal question of whether the intervention improved hand hygiene compliance rates is not part of this article. This is because the next stage of our research is to estimate the cost-effectiveness of the intervention, and because the major costs are attributable to infections, we need to know whether and by how much the intervention reduced infections. Large amounts of money have been invested in the NHHII, so it is important to evaluate whether this money has been well spent, because this evidence should determine its continued funding.

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