compliance among nursing staff have also been described previously.[8]

The limitations of our study were the small sample size and monitoring that did not take into account what occurred inside the patient rooms. In addition, MDs and RNs received instruction from different personnel, so there may have been qualitative differences in the intervention received. Nevertheless, this project shows that despite the use of a rapid-cycle intervention to improve quality of care, improvement will require a concerted and sustained effort that goes beyond education and feedback.

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Reply to Iroh Tam et al

To the Editor—We thank Iroh Tam et al[1] for responding to our work on hand hygiene sampling.[2] Indeed, one of our goals was to encourage more data-driven approaches to inform hand hygiene programs. In our original article, we collected and used spatially and temporally dense "sensor-mote" data to study healthcare worker (HCW) movement and interaction. We used these data to determine where and when to observe hand hygiene behavior in order to best measure compliance (as well as to answer other healthcare-related questions; see Hornbeck et al[3]). Intuitively, periods aligning with the start of shifts or morning rounds seem like good candidates for observation—an intuition our sensor data confirmed is true for the University of Iowa Hospitals and Clinics (UIHC) medical intensive care unit (MICU).

One possible criticism of our previous work relates to the generalizability of our results—that is, how our results can be reliably applied to other healthcare facilities outside the UIHC MICU without sensor-mote data. Because we recognize that it is not feasible for every healthcare facility to replicate our data collection and analysis methods, we propose another simple, inexpensive, data-driven methodology for selecting candidate hours for hand hygiene observation. When validated against our original fine-grained sensor-mote data, we find that this new approach performs very well, resulting in a 1.5–3-fold improvement over just randomly choosing hours for observation (with uniform density).

Our new method relies on using HCW log-ins to electronic health records (EHRs) as a proxy indicator for HCW location and level of activity. Because accessing patient EHR information has become a standard component of patient care, many healthcare facilities now place computer terminals in patient care areas or even in individual patient rooms. Historical records of HCW log-ins are easily retrievable from EHR systems and typically contain the time, user identifiers, and computer terminal identifiers for every log-in event and thus, by extension, the approximate location of the event. In other work, we show how HCW contact networks inferred from such log-in data approximate the quality of networks obtained with more accurate but expensive sensor-mote deployments.[4] This same idea—that log-in records capture many important nonstandard indicators of patient care—can easily be extended to hand hygiene surveillance. Because log-ins linked to computers in patient rooms correlate with actual visits by HCWs vis-à-vis hand hygiene opportunities arising from HCW/patient contact, they can also be used to estimate temporal patterns appropriate for effectively monitoring hand hygiene activity levels.

To validate our new method, we used 660 days of UIHC MICU log-in data (September 1, 2006, through June 21, 2008), restricted to those log-ins linked to patient rooms (a total of 1,757 unique users). We then counted the number of unique users who log in for every hour for each day in our data set. For each day and night shift, we then rank ordered each hour on the basis of the number of unique individual log-ins observed (the choice of this metric was motivated by our simulations of hand hygiene compliance, which show that methodologies that favor observing more unique individuals rather than more events results in a better overall estimate of unit compliance, in essence by reducing sample bias in population selection). The resulting distribution of each hour's respective rank is then calculated across the entire data set and validated against a similar rank-order statistic derived from the sensor-mote data, where each hour in the shift is ranked by median number of captured hand hygiene events.

Overall, we found that the observed hourly, unique HCW log-ins in our sensor data set are highly correlated with the same measure in our log-in data, with a Spearman's ρ of 0.86 ($P < .001$).

Choosing a single observation hour on the basis of log-in rank results in selecting the single best hour 22% and 29% of the time for the day and night shift, respectively, a 2.5–3-fold improvement over simply selecting an hour at random. If we instead select the top quartile of hours per shift, it will contain the best hour 47% and 60% of the time for the day and night shift, respectively, a 1.5–2.5-fold improvement over uniform random selection. More generally, because this approach calculates qualitative rankings for each hour, we can both identify alternate candidate hours for observation (eg, the second-best hour to observe) and identify candidates that are consistently the best hours for observation compared with other, more variable candidate hours. By examining the variability (ie, entropy) of a given hour's rankings, we find that the best hours for observation tend to be those with lower variability for a shift—that is, their rankings are more stable across any given day. As a last point, all these results assume a static choice of observation hour across the entire data set. An obvious improvement would be a dynamic schedule in which an algorithm uses a window of recent log-in data to propose different candidate hours, providing real-time guidance to observers on which hours to monitor. We leave this idea for exploration in future work.

Data-driven approaches are being applied to problems in health care with increasing regularity. Improving hand hygiene observation is one such application. Our results show that human observation schedules can be effectively and inexpensively operationalized using data that healthcare facilities already have on hand.

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Acinetobacter calcoaceticus–Acinetobacter baumannii Complex Is Not Equal to *A. baumannii*

To the Editor—We read with great interest the article by Kang et al[1] that investigated the epidemiology and clinical features of community-onset *Acinetobacter baumannii* infections in a medical center in Korea. In this study, Kang and colleagues provide some significant findings to help clinicians better understand the clinical manifestations of *A. baumannii* in-