White Paper

Estimation of the Impact of Increased Daylight Surface Disinfection Due to the Use of Smart Windows in a Simulated ICU

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Introduction

The purpose of this model was to explore the potential of using "smart windows" that filter sunlight while allowing certain wavelengths of daylight to penetrate a window in lieu of solid barriers such as curtains that effectively block both visible and UV spectrum light. Using a stochastic compartmental model that has been used for several previous studies examining the transmission of MRSA in intensive care units (ICUs), this model estimates the impact on transmission of the increased ambient daylight exposure caused by these windows.

Methods

Model Structure:

The simulated ICU was adapted from a previously published study by Mietchen, Short, Samore and Lofgren, 2019[1] which has been used in a number of other studies examining the dynamics of MRSA infection in ICUs[2] and the estimation of the effect of interventions[3]. Briefly, the unit is a simulated 18-bed ICU, with healthcare workers (HCWs) being comprised of six intensive care nurses and one dedicated intensivist. Each nurse is assigned to three patients, and treats *only* those three patients, while the intensivist sees all patients in the ICU – this assumption is a conservative one in terms of the estimated effect of any intervention (see 1). The structure of this model is shown in Figure 1.

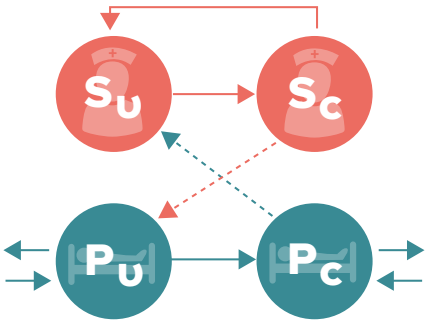

Figure 1. Schematic representation of the compartmental flow of a mathematical model of methicillin-resistant *Staphylococcus aureus* (MRSA) acquisition with a single type of staff. Solid arrows indicate possible transition states, while dashed arrows indicate potential routes of MRSA contamination or colonization (transition parameters found in Table 1). Healthcare staff are classified as uncontaminated (S_U) or contaminated (S_C), while patients are classified as uncolonized (P_U) or colonized (P_C). Model equations are found in Table S1

Hospital staff are either uncontaminated (S_U) or contaminated (S_C), representing infectious material on their hands or person. Patients are either uncolonized (P_U) or colonized (P_C). Patients move from uncolonized to colonized based on encountering a contaminated healthcare worker, and an uncontaminated healthcare worker becomes contaminated by treating a colonized patient and picking up infectious material on their hands or other body sites. They may subsequently become uncontaminated by doffing contaminated PPE and/or washing their hands. A simplified version of this flow is shown in Figure 2. The equations that govern this model may be found in 1.

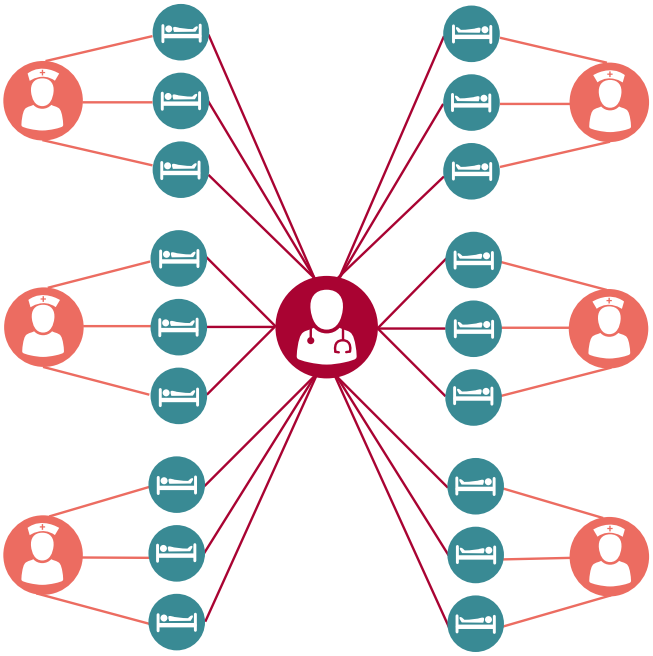

Figure 2. Schematic representation of a Metapopulation model of methicillin-resistant *Staphylococcus aureus* (MRSA) acquisition (transition parameters found in Table 1). Patients (blue) are treated by a single assigned nurse (orange). A single physician (red) randomly treats all patients.

Model Parameterization:

Parameter values were obtained predominantly from a previously published model of MRSA transmission in an ICU based on data from a large, multicenter clinical trial[4,5]. The values of these parameters can be found in Table 1. Contact rates between patients and healthcare workers were represented as direct care tasks per hour for each healthcare worker type (i.e. nurses and the intensivist). A direct care task is defined as the physical interaction of a healthcare worker with the patient or their surrounding environment, which helps account for the possibility of fomite-mediated transmission[6]. Effective hand-decontaminations per hour (ι) were calculated by the number of direct care tasks and taking into consideration the compliance rate and handwashing efficacy. Effective gown and glove changes per hour (τ) were calculated based on the number of visits to a patient per hour and a compliance rate – changing gowns and gloves was assumed to be 100% effective at removing contamination from a healthcare worker.

Model Scenarios:

A baseline scenario, based on previously published work, assumes no daylight surface decontamination processes – i.e. blinds or another method prevents the ambient level of daylight in a room from ever reaching a biologically relevant level. Two "Smart Window" based scenarios were modeled, both assuming some level of filtered, ambient daylight replacing the blocked light in the baseline scenario. This period of ambient light is referred to hereafter as the "decontamination period". The first scenario assumes a decontamination period of 0.85 hours/day, representing the weighted average over 12 months of direct sunlight on a patient's bed, based on simulation results provided by View. The second scenario assumes a slightly longer period of 2.53 hours/day, based on the weighted average over 12 months of direct sunlight on either a patient's day as well as other soft surfaces a visitor or other occupant of the room may be in – and thus trigger the dimming function of the window when direct sunlight strikes.

Two potential mechanisms by which daylight disinfection/decontamination were modeled (for a total of four scenarios). One assumed that daylight primarily cleared existing contamination on a patient or their bedside, thus reducing the likelihood that a healthcare worker's hands become contaminated while treating a colonized patient (σ). The second assumed both this mechanism, as well as disinfecting a patient's skin post-contamination, reducing the likelihood that contact with a contaminated healthcare worker would result in colonization (ψ). In both cases, the effectiveness of daylight was assumed to result in a 98.17% reduction in each parameter, based on results from laboratory testing at the University of British Columbia.

There are several attendant assumptions in these scenarios – that the reduction in bacterial counts based on lab data results in a proportionate decrease in the potential for contamination/colonization (rather than there being thresholds). This assumption is a relatively crude approximation of the actual process. The model also assumes all patients and patient rooms are functionally identical, and that the yearly average amount of light is constant, rather than following seasonal trends.

Table 1. Parameters for modeling the acquisition of methicillin-resistant *Staplylococcus aureus* in an Intensive Care Unit

Parameter	Parameter Description	Parameter Value	Source(s)
ρ	Contact rate between patients and HCWs	4.154 (# of direct care tasks/hour)	[7,8]
ρ_N	Contact rate between patients and nurses	3.973 (# of nurse direct care tasks/hour)	[7,8]
ρ_D	Contact rate between patients and physician	0.181 (# of physician direct care tasks/hour)	[7,8]
σ	Probability that a HCW's hands are contaminated from a single contact with a colonized patient	0.054	[9]
ψ	Probability of successful colonization of an uncolonized patient due to contact with a contaminated HCW in metapopulation structure	0.4481	Fitted to [4]
θ	Probability of discharge	4.39 $days^{-1}$	[4]
ν_u	Proportion of admissions uncolonized with MRSA	0.9221	[4]
ν_c	Proportion of admissions colonized with MRSA	0.0779	[4]
ι	Effective hand-decontaminations/hour (direct care tasks × hand hygiene compliance × efficacy)	5.740 (10.682 direct care tasks/hour × 56.55% compliance × ~ 95% efficacy)	[4,7,8,10]
ι_N	Effective nurse hand-decontaminations/hour	6.404 (11.92 direct care tasks/hour × 56.55% compliance × ~ 95% efficacy)	[4,7,8,10]
ι_D	Effective physician hand-decontaminations/hour	1.748 (3.253 direct care tasks/hour × 56.55% compliance × ~ 95% efficacy)	[4,7,8,10]
τ	Effective gown or glove changes/hour (2 × # of visits × compliance)	2.445 (2.957 changes/hour × 82.66% compliance)	[4,9,11]
τ_N	Effective nurse gown or glove changes/hour	2.728 (3.30 changes/hour × 82.66% compliance)	[4,9,11]
τ_D	Effective physician gown or glove changes/hour	0.744 (0.90 changes/hour × 82.66% compliance)	[4,9,11]
μ	Natural decolonization rate	20.0 $days^{-1}$	[12]

Model Implementation

The primary outcome of each scenario was the number of incident MRSA acquisitions in a single year. The models were stochastically simulated using Gillespie's Direct Method[13] in Python 3.6 using the StochPy package[14] for 5,000 iterations per scenario. The initial conditions for each model were set to have no contaminated healthcare workers, either nurses or the physician, and a single colonized patient. The distribution of the acquisitions for each model's 5,000 iterations was visualized in R v3.5.1 using the vioplot package[15], and the difference between them assessed using a Kruskal-Wallis test, as the results of the model were likely to be non-normal.

Results

The results of the five different scenarios are summarized in Table 2, below. All results are reported as the median number of incident MRSA acquisitions per 1,000 Patient-Days.

Table 2. Incident methicillin-resistant *Staphylococcus aureus* infections in five potential scenarios.

Scenario	Acquisitions per 1,000 Patient-Days	% Change	p-value
Baseline	8.94	-	-
Dimming for Bed Only			
Sigma-Only	8.69	-2.8%	0.1
Sigma and Psi	8.51	-4.8%	0.006
Dimming for Bed and Seating Surfaces			
Sigma-Only	7.94	-11.2%	<0.001
Sigma and Psi	7.76	-13.2%	<0.001

Briefly, all scenarios had a reduction in overall MRSA acquisition rates, with the longer duration of the decontamination period (i.e. 0.85 hours/day vs. 2.53 hours/day) having a larger impact on the results of the model than which potential mechanisms of action (i.e. reducing HCW contamination vs. reducing both HCW contamination and the probability of patient colonization given contaminated contact). In all scenarios, the distribution of results are heavily weighted toward zero, given the small numbers and the underlying assumption of the model that the ICU is otherwise relatively effectively controlling MRSA infections, with a long tail of rare but serious outbreaks. The scenarios assuming the presence of smart windows had markedly shorter tails (Figures 3 and 4).

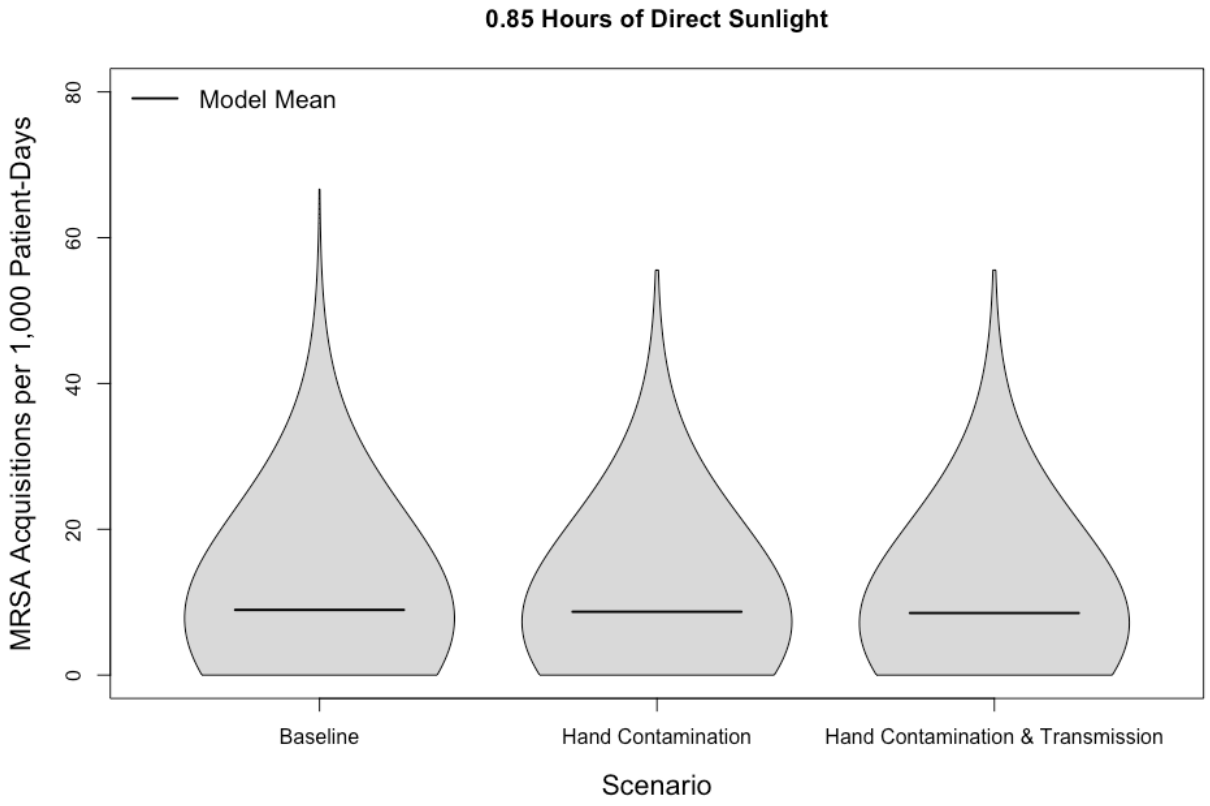

Figure 3. Distribution of 5,000 simulated methicillin-resistant *Staphylococcus aureus* acquisitions over a single year in an intensive care unit, with 0.85 hours/day of ambient daylight. Solid black bars represent the median result, while the "Hersey's Kiss" is a kernel-smoothed density of the entire distribution.

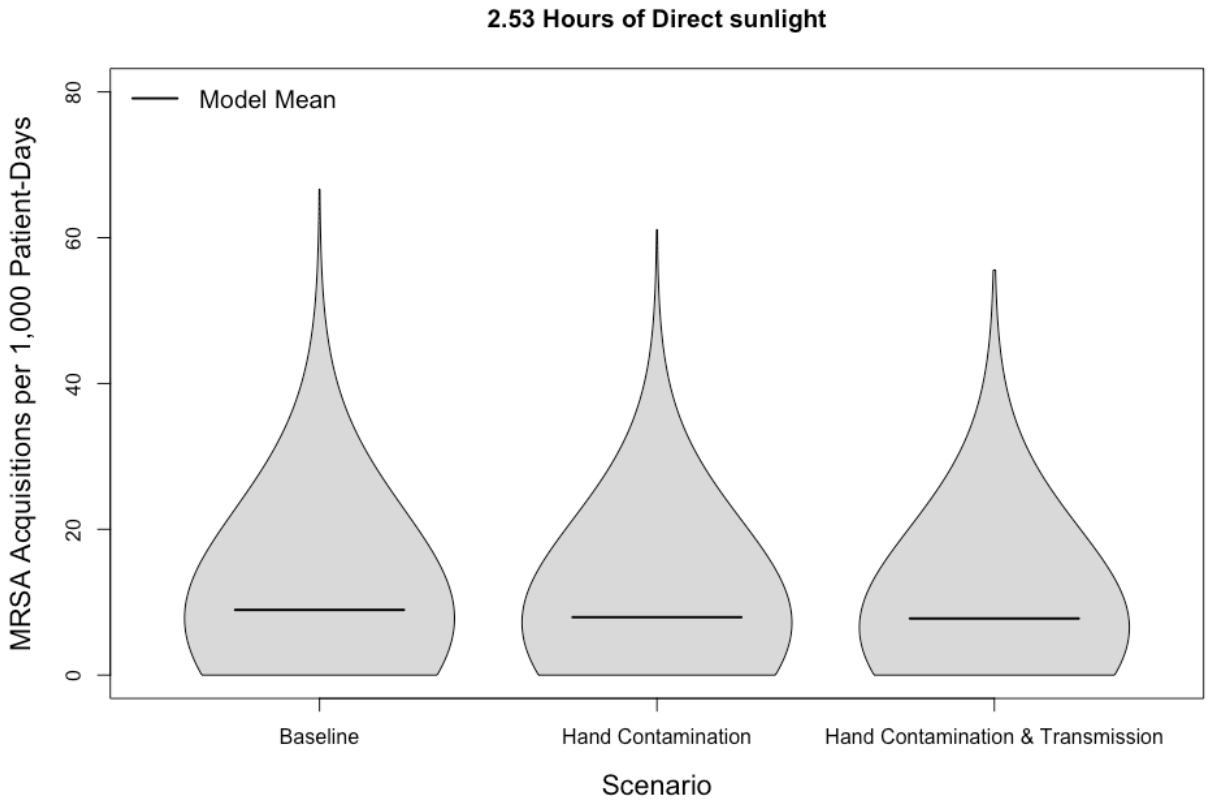

Figure 4. Distribution of 5,000 simulated methicillin-resistant *Staphylococcus aureus* acquisitions over a single year in an intensive care unit, with 2.53 hours/day of ambient daylight. Solid black bars represent the median result, while the "Hersey's Kiss" is a kernel-smoothed density of the entire distribution.

Discussion and Conclusion

The results of these simulations suggest that the use of smart windows that effectively filter sunlight while allowing shorter wavelength, higher energy daylight to penetrate the window may have a modest but clinically meaningful impact on healthcare-associated infections, by providing a period of consistent, passive sanitization and sterilization of both the patient and their immediate environment. While these results are statistically significant in a sample of 5,000 simulated ICUs per scenario, it is unlikely that any given ICU or even multiple ICUs in the same facility will have the power to detect the resultant changes, especially for the more conservative scenarios, such as windows only benefitting the room 0.85 hours/day or only impacting the transmission of fomites to healthcare worker hands.

As discussed above, and as with all simulation models, there are several caveats and assumptions that go into these results. The proposed mechanism of action modeled here is relatively course, assuming a linear relationship between a reduction in organisms and the potential for contamination/colonization. Similarly, this model focuses primarily on the direct interaction between a healthcare worker and a patient and/or that patient's immediate environment, with environmental contamination elsewhere in the room assumed to represent a negligible source of infection risk. Should this not be the case, the model may fail to fully capture the impact of an increased amount of ambient daylight. Similarly, this model considers

only a single organism, while the actual impact of the proposed windows should impact all organisms susceptible to radiation in the near UV range. This was chosen to leverage an existing implemented and validated model, and *S. aureus* infections are among the most common infections in hospitals. Finally, the decontamination period is, for simplicity, a constant based on the average light a room receives over the course of the year, rather than fluctuating seasonally, or varying by the facing of each individual room. The former can be addressed within the code for the model.

Several of the scenarios in this model are based on fairly conservative assumptions, both in terms of the model itself (i.e. nurses are strictly assigned to their three patients) and in some of the scenarios, where the mechanisms by which ambient daylight for longer periods of the day are assumed to be both relatively brief and have fairly restrictive mechanisms of action. Despite this, even in those scenarios, reductions in cases can be seen. In scenarios that allow for longer periods in which the shades of a room might be drawn or make slightly less conservative assumptions about the ways in which increased ambient daylight impact the transmission dynamics of *S aureus*, these reductions begin to exceed 10%. These results may be useful for informing power calculations for empirical studies, initial estimates for cost-effectiveness models, or a baseline for more granular modeling efforts. Overall, this study suggests that the addition of smart windows to ICU rooms may present a compelling passive and horizontal intervention to supplement other infection control efforts.

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