Modeling the impact of interventions against Acinetobacter baumannii transmission in intensive care units

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Keywords: Acinetobacter baumannii, infection control, intensive care units, mathematical modeling, transmission dynamics

Abbreviations: CFU, colony-forming unit; ICU, intensive care unit; LoS, length of stay

The efficacy of infection control interventions against Acinetobacter baumannii remains unclear, despite such information being critical for effective prevention of the transmission of this pathogen. Mathematical modeling offers an alternative to clinical trials, which may be prohibitively expensive, unfeasible or unethical, in predicting the impact of interventions. Furthermore, it allows the ability to ask key "what if" questions to evaluate which interventions have the most impact. We constructed a transmission dynamic model to quantify the effects of interventions on reducing A. baumannii prevalence and the basic reproduction ratio (R₀) in intensive care units (ICUs). We distinguished between colonization and infection, and incorporated antibiotic exposure and transmission from free-living bacteria in the environment. Under the assumptions and parameterization in our model, 25% and 18% of patients are colonized and infected with A. baumannii, respectively; and R₀ is 1.4. Improved compliance with hand hygiene (≥87%), enhanced environmental cleaning, reduced length of ICU stay of colonized patients (≤10 days), shorter durations of antibiotic treatment of A. baumannii (≤6 days), and isolation of infected patients combined with cleaning of isolation rooms are effective, reducing R₀ to below unity. In contrast, expediting the recovery of the intestinal microbiota (e.g. use of probiotics) is not effective. This study represents a biologically realistic model of the transmission dynamics of A. baumannii, and the most comprehensive analysis of the effectiveness of interventions against this pathogen. Our study provides important data for designing effective infection control interventions.

Introduction

Acinetobacter baumannii is a leading cause of severe infections, such as ventilator-associated pneumonia, bacteremia, urinary tract infections and meningitis, in patients in intensive care units (ICUs).¹ Infections caused by A. baumannii are difficult to treat because it is resistant to many antibiotics.² As such, limiting the emergence and spread of this pathogen is of paramount importance.

The acquisition and spread of A. baumannii is a complex and dynamic process determined by various inter-related factors. Exposure to antibiotics and the resultant disruption of the intestinal microbiota are known to predispose to A. baumannii acquisition.³ Other major contributing factors for the acquisition of A. baumannii in ICUs include patient-related factors such as use of invasive procedures, and ICU-related factors such as transmission between patients within the ward (cross-transmission).⁴,⁵ Furthermore, A. baumannii can remain viable in the hospital environment for a prolonged period of time, serving as an important reservoir and contributing to acquisition by susceptible patients (environment-patient transmission).⁶,⁷ As such, a multifaceted approach which encompasses reducing cross-transmission, environment-patient transmission and antibiotic exposure could be required to limit the acquisition and spread of this pathogen. However, the relative contribution of each component remains unclear. Historically, such data can be obtained by conducting clinical and epidemiological studies. However, these studies are time-consuming and may be prohibitively expensive in the hospital setting. Operational and/or ethical constraints may further limit whether interventions can be evaluated in clinical studies. Additionally, these studies are inherently unable to capture the interdependence between individuals. As such, these studies only provide individual patient-level data and fail to fully characterize the transmission dynamics of the pathogen.

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Submitted: 06/05/2015; Revised: 07/17/2015; Accepted: 07/21/2015
http://dx.doi.org/10.1080/21505594.2015.1076615
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Population-level mathematical models, by providing a theoretical framework to conceptualize the dynamic interactions between interdependent variables, can overcome the aforementioned challenges. They provide important insights into the underlying dynamics of an infection; and enable us to quantify the potential impact of various interventions without conducting those interventions. Mathematical models also allow us to test “what-if” scenarios for the design of optimal intervention strategies. While various models have investigated the effects of interventions against Gram-positive pathogens, data on the population-level impact of interventions against A. baumannii (and other Gram-negative organisms alike) are scant. To date, there are only 2 modeling studies that investigate the transmission dynamics of A. baumannii. Although both studies provide important insight into the spread of this pathogen, they have limitations. In our previous model, environment and interventions were not considered; whereas the model by Wang et al. did not distinguish between colonization and infection, nor did it take into account the effects of antibiotic exposure. Furthermore, nurse cohorting and nurse-patient ratio were the only interventions investigated in Wang et al.

Consequently, we have developed a comprehensive mechanistic model to describe the transmission dynamics of A. baumannii in ICUs, and to quantify the effects of various interventions on reducing A. baumannii transmission. Unlike most previous models, we have differentiated between patients colonized and infected with A. baumannii, and incorporated the important role of antibiotic exposure and free-living bacteria in the environment.

**Materials and Methods**

**Mechanistic transmission dynamic model**

A mechanistic model was developed to describe the transmission dynamics of A. baumannii in a hypothetical 100-bed ICU (Fig. 1). In this model, patients were in 5 mutually exclusive states according to their infection status: uncolonized without or with antibiotic exposure (U and UA, respectively), colonized without or with antibiotic exposure (C and CA, respectively), or clinically infected (I). Antibiotic exposure was defined as currently receiving any systemic antibiotic or having received antibiotics within the last 30 d. Colonized and infected patients harbor the pathogen; however only infected patients manifest clinical symptoms. Patients could be admitted to the ICU in any of these 5 states. Of new admissions, 57.6% and 36.8% were uncolonized without and with antibiotic exposure, respectively; and 0.3% and 5.3% were colonized without and with antibiotic exposure, respectively. New admissions that were already clinically infected with A. baumannii were 0%. Patients could be discharged from any compartment, except for the infected compartment where they were manifesting symptoms. Discharge occurred at a rate of γ per day, calculated as the inverse of the length of ICU stay (hereinafter referred to as length of stay, LoS) specific for each compartment. Uncolonized and colonized patients, irrespective of their antibiotic exposure status, stayed in the ICU for an average of 5.5 and 16.5 d, respectively. We assumed that the ICU was fully occupied, and that new admissions balanced discharges, resulting in a constant population size of N = U + UA + C + CA + I = 100.

The movement from uncolonized or colonized without antibiotic exposure (U, C, respectively) to the corresponding compartments with antibiotic exposure (UA, CA, respectively) occurred at a rate of ε = 0.12 per day (antibiotic prescribing rate), which calibrated to 59.5% of ICU patients being prescribed antibiotics (for reasons other than treatment of A. baumannii infection) at any time during their stay. The reverse process (moving from UA to U, and from CA to C) occurred when a patient’s intestinal microbiota recovered after discontinuation of antibiotics, which was assumed to take 35 d. The recovery rate of the intestinal microbiota, λ, was calculated as the inverse of this recovery time (λ = 0.03 per day). The use of probiotics was assumed to act by expediting this recovery process.

Uncolonized patients could become colonized via cross-transmission between patients within the ICU. This acquisition process was determined by the cross-transmission coefficient,
Table 1. Baseline input values of model variables

| Variable | Definition (unit) | Baseline value | Reference |
|----------|------------------|---------------|-----------|
| $\varepsilon$ | Antibiotic prescribing rate (/day)$^a$ | 0.12 | 23,24 |
| $\lambda$ | Recovery rate of intestinal microbiota (/day) | 0.03 | 25 |
| $\beta$ | Cross-transmission coefficient (/colonized/susceptible/day) | $50 \times 10^{-4}$ | 4 |
| $\xi$ | Environment-patient transmission coefficient (/CFU/susceptible/day) | $4 \times 10^{-6}$ | 30 |
| $\Omega_1$ | Infectivity of $C_A$ relative to $C$ | 1.67 | 29 |
| $\Omega_2$ | Infectivity of $I$ relative to $C$ | 2 | 29 |
| $\theta_A$ | Rate of $C_A$ becoming infected (symptom development rate) (/day) | 0.11 | 5 |
| $\theta$ | Rate of $C$ becoming infected (symptom development rate) (/day) | $\theta_A/5$ | 32 |
| $\tau$ | Treatment of $A. baumannii$ infection (/day) (1/antibiotic treatment duration of infected patients) | 0.08 | 33,34 |
| $\sigma$ | Treatment success rate of $A. baumannii$ infection (/treated patient) | 0.76 | 34 |
| $\eta$ | Rate of self-resolution of symptoms (/day)$^b$ | 0.018 | 35 |
| $f$ | Fatality rate of infected patients (/day)$^c$ | 0.016 | 36 |
| $r$ | Environmental cleaning rate (/day) | 0.70 | 30 |
| $\alpha$ | Efficacy of environmental cleaning (/CFU) | 0.55 | 31 |
| $h$ | Compliance with hand hygiene | 0.82 | 27 |
| $\gamma_U$, $\gamma_{UA}$ | Discharge rate of $U$ and $UA$ (/day) | 0.18 | 19,20 |
| $\gamma_C$, $\gamma_{CA}$ | Discharge rate of $C$ and $CA$ (/day) | 0.06 | 21,22 |
| $\Lambda$ | Admission rate (/day) | Rate of leaving the ICU$^d$ |
| $\mu_U$, $\mu_{UA}$ | Proportion of $U$ and $UA$ on admission | 57.6%; 36.8% | 16 |
| $\mu_C$, $\mu_{CA}$ | Proportion of $C$, $CA$ and $I$ on admission | 0.3%; 5.3%; 0% | 16,17 |
| $\Phi_1$, $\Phi_2$, $\Phi_3$ | Proportion of $C$, $CA$ and $I$ (CFU/patient/day) | 281; 470; 563 | 30 |

$^a$Calibrates to 59.5% of patients receiving antibiotics any time during their ICU stay.
$^b$Calibrates to 15% of infected patients having symptoms that self-resolve.
$^c$Calibrates to 14% attributable mortality rate.
$^d$Admission rate, $\Lambda = \gamma_U U + \gamma_{UA} U_A + \gamma_C C + \gamma_{CA} C_A + \mu_U$.

Colonized patients with antibiotic exposure became infected (movement from $C_A$ to $I$) at a rate of $\theta_A = 0.11$ per day.$^e$ Colonized patients without antibiotic exposure were assumed to be 5-times less likely to become infected than those with antibiotic exposure.$^a$ Antibiotic treatment of patients infected with $A. baumannii$ was assumed to take 13 d ($\tau = 13$) with a successful clearance rate of $\sigma = 0.76$ per treated patient.$^b$ Infected patients who were successfully treated and cleared of the pathogen returned to the uncolonized with antibiotic exposure compartment; whereas the remaining treated patients returned to the colonized with antibiotic exposure compartment. Fifteen percent of the patients returned to the uncolonized with antibiotic exposure compartment. 

Table 2. Variation range for variables evaluated in sensitivity analysis

| Variable | Symbol | Range | Reference |
|----------|--------|-------|-----------|
| Treatment success rate of $A. baumannii$ infection | $\sigma$ | 0.6–0.9 | 34 |
| Rate of self-resolution of symptoms | $\eta$ | 0.018–0.022 | ±10% |
| Cross-transmission coefficient | $\beta$ | 39–71 $\times 10^{-4}$ | 4 |
| Environment-patient transmission coefficient | $\xi$ | 3.4–4.6 $\times 10^{-6}$ | 30 |
| Fatality rate of infected patients$^a$ | $f$ | 0.006–0.020 | 36,55 |
| LoS of colonized patients | $\nu_C$ | 7–25 | 4,43 |

$^a$Calibrates to 6% and 17% attributable mortality rate, respectively. LoS, length of stay.
and infected patients, and the basic reproduction ratio, \( R_0 \) and 14% of infected patients died as a result of the disease.\(^{36}\) Table 1 summarizes the input values of the model variables with their definitions and references. The system of ordinary differential equations that describe the transition between compartments is as follows:

\[
\begin{align*}
\frac{dU}{dt} &= \lambda U_U + \lambda U_A - \frac{U beta(1-h)(C + \Omega_1 C_A + \Omega_2 I)}{N} - \gamma U_U - \varepsilon U - \zeta (1-h) EU; \\
\frac{dU_A}{dt} &= \lambda U_A + \varepsilon U + \sigma I - \frac{U_A beta \times 1.67 \times (1-h)(C + \Omega_1 C_A + \Omega_2 I)}{N} - \lambda U_A - \gamma U_A U_A - \zeta (1-h) EU_A; \\
\frac{dC}{dt} &= \lambda C_A + \varepsilon C_A + \frac{U beta(1-h)(C + \Omega_1 C_A + \Omega_2 I)}{N} - \varepsilon C - \gamma C A - \theta C + \zeta (1-h) EU; \\
\frac{dC_A}{dt} &= \lambda C_A + \varepsilon C_A + \frac{U_A beta \times 1.67 \times (1-h)(C + \Omega_1 C_A + \Omega_2 I)}{N} + (1-\sigma)I + \eta I - \gamma C A C_A - \lambda C_A - \theta A C_A + \zeta (1-h) EU_A; \\
\frac{dI}{dt} &= \lambda I + \theta C + \theta A C_A - fI - \eta I - \sigma I - (1-\sigma)I; \\
\frac{dE}{dt} &= \Phi_1 C + \Phi_2 C_A + \Phi_3 I - r\alpha E.
\end{align*}
\]

The model was simulated for one year (365 days). The following outcome measures were estimated: prevalence of colonized and infected patients, and the basic reproduction ratio, \( R_0 \). Briefly, \( R_0 \) is the average number of secondary colonized cases resulting from one single infectious individual in a totally susceptible population.\(^{37}\) It is an important predictor of whether and how quickly an infection will spread. The aim of any intervention is to reduce \( R_0 \) to below unity. The next generation matrix method (described in Appendix 1) was used to estimate \( R_0 \) in our study.\(^{38}\)

### Interventions

Simulations were performed to evaluate the efficacy of various interventions in reducing the prevalence of colonized and infected patients, and \( R_0 \). The following interventions were investigated:

1. improved compliance with hand hygiene (\( h \));
2. reduced antibiotic prescribing rate (\( e \));
3. reduced antibiotic treatment duration in patients infected with \( A. \) baumannii (\( \tau \));
4. improved recovery rate of the intestinal microbiota (\( r \));
5. LoS of colonized patients (\( \gamma_u \));
6. increased environmental cleaning rate (\( r \), more frequent cleaning);
7. improved environmental cleaning efficacy (\( \alpha \), e.g., more effective cleaning products, training for cleaning teams); and
8. isolation of infected patients combined with cleaning of isolation rooms.

### Sensitivity analysis

Multivariate sensitivity analysis was carried out to investigate the key drivers of the outcome measures and the sensitivity of model outputs to changes in model inputs. The following variables were assessed: success rate of \( A. \) baumannii treatment (\( \sigma \)), rate of self-resolution of symptoms (\( \eta \)), fatality rate of infected patients (\( f \)); and LoS of colonized patients (\( \gamma_u \)). The range of each variable is shown in Table 2. The Latin hypercube sampling method was performed. Partial rank correlation coefficients were calculated to evaluate the

![Figure 2. Prevalence of patients colonized and infected with A. baumannii at baseline.](image)

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**Table 1**

| Parameter | Value |
|-----------|-------|
| \( \lambda \) | 0.3 |
| \( \mu \) | 0.1 |
| \( \varepsilon \) | 0.05 |
| \( \gamma \) | 0.02 |
| \( \zeta \) | 0.01 |
| \( \sigma \) | 0.01 |
| \( \eta \) | 0.005 |
| \( \theta \) | 0.002 |
| \( \rho \) | 0.001 |
| \( \Phi_1 \) | 0.002 |
| \( \Phi_2 \) | 0.001 |
| \( \Phi_3 \) | 0.0005 |
| \( \Omega \) | 0.0005 |

**Table 2**

| Variable | Low Value | High Value |
|----------|-----------|------------|
| \( \lambda \) | 0.1 | 0.5 |
| \( \mu \) | 0.05 | 0.2 |
| \( \varepsilon \) | 0.04 | 0.06 |
| \( \gamma \) | 0.01 | 0.03 |
| \( \zeta \) | 0.005 | 0.015 |
| \( \sigma \) | 0.005 | 0.015 |
| \( \eta \) | 0.001 | 0.005 |
| \( \theta \) | 0.001 | 0.005 |
| \( \rho \) | 0.0005 | 0.0015 |
| \( \Phi_1 \) | 0.0015 | 0.0025 |
| \( \Phi_2 \) | 0.001 | 0.002 |
| \( \Phi_3 \) | 0.0005 | 0.001 |
| \( \Omega \) | 0.0005 | 0.0015 |
strength of the correlation between each outcome measure and each variable. All analysis was performed using MATLAB (version R2015a, MathWorks, Natick, MA, USA). The differential equations were solved using the \texttt{ode45} solver.

**Results**

**Baseline scenario**

Using the baseline parameters (Table 1), we estimate that 25% of patients are colonized, and 18% are infected with \textit{A. baumannii} (Fig. 2). Acquisition is predominantly caused by within-hospital transmission (98%), rather than colonization already present on admission. $R_0$ is estimated to be 1.4.

The impact of interventions

Figure 3 shows the predicted effects of individual interventions on reducing the prevalence of \textit{A. baumannii} and $R_0$. The relative effects among the interventions investigated are shown in Figure 4. Compliance with hand hygiene ($h$) is the most effective intervention whereby a modest improvement in compliance rate, from 82% (baseline) to 87%, reduces $R_0$ from 1.4 to unity, and reduces the prevalence of colonized and infected patients by 6% (from 25% to 19%) and 4% (from 18% to 14%), respectively (Fig. 3A). In an idealized scenario where compliance rate is 100%, $R_0$ is reduced to zero; however, \textit{A. baumannii} always persists at a low level (Fig. 5A). This is because of the constant admission of colonized patients into the ICU, with 5.6% of admitted patients already colonized at baseline. Figure 5A shows that when colonized patients are not admitted, \textit{A. baumannii} will become extinct when $R_0$ is below unity. When $R_0$ is above unity, \textit{A. baumannii} is always endemic irrespective of whether colonized patients are admitted (Fig. 5B).

Frequent ward cleaning ($r$) is also an effective intervention (Fig. 3B). Increasing environmental cleaning rate from 0.7 (baseline) to 1 (daily cleaning) reduces the prevalence of colonized and infected patients from 25% to 19% and from 18% to 14%, respectively. Daily ward cleaning also reduces $R_0$ to unity. Similar
reductions can be achieved when the efficacy of environmental cleaning (α) is improved from 55% (baseline) to 75% (Fig. 3C). Figures 6A and B show the combined effects of enhanced cleaning rate and cleaning efficacy. Combining the 2 interventions yields improved benefits compared to each intervention alone. For example, daily ward cleaning combined with improved cleaning efficacy (from 55% to 75%) reduces the total prevalence of colonization and infection by 18%, compared to 10–11% reduction achievable with each intervention alone. Isolation of infected patients has modest effects (Fig. 4). However, isolation combined with cleaning of isolation rooms is effective, significantly reducing the prevalence of colonized patients from 25% (baseline) to 14%, and the prevalence of infected patients from 18% (baseline) to 11%. With this strategy, $R_0$ is 0.7 (Fig. 4).

Figure 3D shows the effects of reducing the LoS of colonized patients ($\gamma_C^{-1}$). The prevalence of $A. baumannii$ decreases with shorter LoS (increased discharge rate). Specifically, when the LoS is reduced from the baseline of 16.5 d to 10 days, $R_0$ reduces to below unity, and the prevalence of colonization and infection reduces by 7% (from 25% to 18%) and 5% (from 18% to 13%), respectively.

When antibiotic prescribing rate (ε) among ICU patients (for reasons other than treatment of $A. baumannii$ infection) and antibiotic treatment duration of infected patients ($\tau^{-1}$) are investigated separately, only the latter is effective. Reducing antibiotic prescribing rate from 0.12 (baseline) to 0 (no antibiotic use) only results in a 4% reduction in the total prevalence of colonized and infected patients (Fig. 3E). In contrast, similar reductions in antibiotic treatment duration of infected patients ($\tau^{-1}$, from 13 d to 5 days) decrease the total prevalence of colonized and infected patients by 14% (from...
43% to 29%) and $R_0$ to unity (Fig. 3F). This intervention has greater effects on the prevalence of infected patients than on colonized patients because it specifically targets the former (Fig. 3F). Combining the 2 interventions fails to yield any improvements in reducing *A. baumannii* prevalence compared to each intervention alone (Figs. 6C and D). For example, simultaneously reducing antibiotic prescribing rate from 0.12 to 0 and antibiotic treatment duration of infected patients from 13 d to 5 d only results in a 14% reduction in the total prevalence of colonized and infected patients. Comparable reduction would be achievable with reduced antibiotic treatment duration of infected patients alone.

The use of probiotics to expedite the recovery of the intestinal microbiota ($\lambda_1$, 1/recovery time) is not effective. Reducing the recovery time from 35 d to 14 d only reduces the total prevalence of colonization and infection by 1% (Fig. 3G). No enhanced effects are achieved when probiotics are used in conjunction with reduced antibiotic prescribing rate (Figs. 6E and F).

**Varying transmission coefficients**

Figure 7 shows the effects of varying the cross-transmission coefficient ($\beta$) or environment-patient transmission coefficient ($\zeta$) on the prevalence of *A. baumannii* and $R_0$. Contaminated environment is the predominant acquisition source compared to cross-transmission. Complete elimination of environment-patient transmission ($\zeta = 0$) generates substantial benefits, reducing the prevalence of colonization from 25% to 7% and infection from 18% to 6%. Eliminating this transmission source reduces $R_0$ to zero. In contrast, only modest impact occurs when cross-transmission is limited.

**Sensitivity analysis**

Figure 8 shows the sensitivity of the outcome measures to changes in model inputs. The outcome measures are most sensitive to LoS of colonized patients ($\gamma_C^{-1}$), *A. baumannii* treatment success rate ($\sigma$), environment-patient transmission coefficient ($\zeta$) and fatality rate of infected patients ($f$). The correlation coefficients are shown in Table 3.

**Discussion**

Our study represents the most comprehensive transmission dynamic model for *A. baumannii*. Unlike previous studies,7,9,11,13,14,41 we differentiated between colonized and infected patients because of their differences in clinical characteristics, particularly in pathogenesis, infectivity and infection control management. Under the baseline values found from review of the literature, we predict that *A. baumannii* is likely to be endemic in ICUs. The estimated prevalence of colonization and infection is 25% and 18%, respectively. Although we did not calibrate our model to any outcome
values, our estimates are comparable with the mean values of the prevalence of _A. baumannii_ colonization (21%)\(^4,16,42,43\) and infection (16%)\(^5,42,44\) reported in the literature. We found that _A. baumannii_ transmission continues even when _R_\(_0\) is below unity owing to admission of already colonized patients to the ICU. Our finding suggests that active screening on admission and subsequent isolation of positive cases is an essential component of any infection control policy to eliminate the transmission of this pathogen. Although this strategy may be effective in controlling _A. baumannii_, active screening is currently not in place in most hospitals worldwide. This may be due in part to concerns about the high costs of implementing such programs.\(^8\) Nevertheless, a comprehensive cost-effectiveness analysis of active screening programs is needed.

Hand hygiene is the most effective intervention in our study because it limits both the transmission between patients and, between patients and the environment. The rate of compliance with hand hygiene was set at 82% at baseline in line with Australian data.\(^27\) Although it is effective, inexpensive and simple, compliance with hand hygiene remains obstinately low in some settings, with estimated compliance rates as low as 50%.\(^45\) When this compliance rate was considered, the prevalence of colonization, infection, and _R_\(_0\) were estimated to be 44%, 31%, and 3.7, respectively. Using Figure 3A, predictions of _A. baumannii_ prevalence and _R_\(_0\) could be obtained for any level of hand hygiene compliance. Our model predicts that a modest improvement in compliance rate, from 82% to 87%, will reduce _R_\(_0\) to below unity. Previous studies have shown that such improvements would be achievable with increased education and training, increased availability of alcohol-based hand rubs, workplace reminders, and performance feedback.\(^45\)

Our model also shows that shorter durations of antibiotic treatment in patients infected with _A. baumannii_ are associated with lower prevalence of _A. baumannii_. This suggests that treating patients as quickly and effectively as possible may be an effective strategy. Indeed, previous clinical studies have shown that the durations of antibiotic therapy could be safely reduced to ≤7 d based on clinical, laboratory, and radiologic measures without any adverse effects on patient’s outcomes while reducing the prevalence of infection and resistance.\(^46-48\) These findings emphasize the importance of effective antimicrobial stewardship programs in reducing the duration of antibiotic therapy. However, it should be noted that the translation of the findings of these studies into clinical practice is currently unknown; and that the optimal durations of antibiotic treatment for many common infections remain to be established. Effective antimicrobial stewardship programs can also lead to reductions in antibiotic usage.\(^49\) However, we found that reducing antibiotic prescribing rate among patients who are not infected with _A. baumannii_ has a modest impact on _A. baumannii_ prevalence, consistent with previous studies.\(^12,18\) This is because this strategy only targets the small subset of patients who are uncolonized or colonized without prior antibiotic exposure in our model.

Clinical evidence on the efficacy of probiotics in reducing infections is inconclusive. It has been shown to be beneficial in some studies,\(^50\) while others have shown minimal effects.\(^51\) Our model suggests that using probiotics has a modest impact on the population-level transmission dynamics of _A. baumannii_, consistent with previous clinical studies.\(^51\) Nevertheless, our finding does not necessarily negate the health benefits of these products on an individual-patient level.\(^26\)

We found that reducing LoS is effective in attenuating _A. baumannii_, in support of evidence from clinical studies and previous models.\(^10,18,52\) This is because this strategy reduces patient’s risk factors for acquiring _A. baumannii_ in the ICU.\(^16\) Our finding is in contrast with Cooper et al.\(^28\) who demonstrated in their model that shorter LoS resulted in higher within-ward colonization.\(^28\) This may be explained by the increased number of susceptible patients admitted to the ward as a result of reduced LoS (increased discharge rate). Nevertheless, it should be noted that LoS of patients should be based on their clinical characteristics and response to treatment. As such, reducing LoS is likely to be impractical in reality.

The current model incorporates transmission from free-living bacteria in the environment, which has been ignored in the majority of previous models.\(^4,9-12,18,53\) We found that
contaminated environment is the major source of acquisition. Our finding reinforces the importance of environmental cleaning in controlling health-care associated infections as previously shown in clinical studies.\textsuperscript{31,54} We found that improving the effectiveness of environmental cleaning would substantially reduce \textit{A. baumannii}. This could be achieved by using more effective cleaning products, training and monitoring the efficacy of decontamination with feedback to cleaning teams. In our

\textbf{Figure 8.} Sensitivity analysis.
model, free-living bacteria in the ICU were assumed to be uniformly distributed. In fact, bacterial density may be different between places in the ICU (e.g., environment versus computer keyboards or door knobs). Future models that take into account the heterogeneity in contamination status are needed. Direct transmission between patients and free-living bacteria in the environment should also be considered in future studies.

Our study represents a biologically realistic model for the transmission dynamics of *A. baumannii* in ICUs. It provides a comprehensive analysis of the impact of interventions against this pathogen. We have incorporated crucial factors to the epidemiology of this pathogen such as antibiotic exposure, transmission from contaminated environment and, distinguishing colonization and infection. Like most biologically realistic simulation models, we were unable to simulate a specific setting because there is no single clinical study that provides complete parameterization for our model. Importantly, our model provides a framework that can be easily adjusted when such studies become available. Given that the epidemiology of *A. baumannii* varies considerably over time and between different settings, the intention of our model is not to provide numerical estimates that apply to every setting. However, our model can be adjusted to incorporate institution-specific data to guide infection control. Our model can be modified to integrate greater complexity such as co-morbidities, immune status, antibiotic resistance, co-infection with other pathogens, and the effects of stochasticity.

### Disclosure of Potential Conflicts of Interest

D.C.M.K. has sat on advisory boards of Pfizer, Merck Sharp & Dohme, and receives financial/travel support (unrelated to the current work) from Pfizer, Roche, Merck Sharp & Dohme, Novartis and Gilead Sciences. C.M.J.K. has undertaken collaborative research projects unrelated to the current work with Roche, Pfizer, CSL and d3 Medicine. All other authors have no potential conflicts of interest to disclose.

### Funding

T.N.D. is a recipient of the Monash Graduate Scholarship and Monash International Postgraduate Research Scholarship. E. S.M. has received financial support from the Australian National Health and Medical Research Council (NHMRC) Career Development Fellowship. All other authors: none to declare.

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Appendix 1 The next generation matrix for estimating the basic reproduction number, \( R_0 \)

The next generation matrix method involves linearizing the original nonlinear ordinary differential equations at disease-free equilibrium.\(^{38}\) At the disease-free equilibrium, \( X^* \), the numbers of individuals in each compartment are given by:

\[
X^* = \left\{ U^* = \frac{-\lambda N - \gamma_{UA} N \mu_U}{\gamma_U \mu_U - \gamma_{UA} M_U - \lambda - \gamma_U - \epsilon}, \quad V^* = N - U^*, \quad C^* = 0, \quad C_A^* = 0, \quad I^* = 0 \right\}.
\]

Let \( F \) be the transmission matrix, describing the production of new infections; and \( V \) be the transition matrix, describing changes in state (including removal by discharge or death). \( F \) and \( V \) are defined as follows:

\[
F = \left[ \frac{\partial F_i(X)}{\partial X_j} \right]_{X = X^*}, \quad \text{and} \quad V = \left[ \frac{\partial V_i(X)}{\partial X_j} \right]_{X = X^*},
\]

where \( F_i(X) \) is the number of new infections in the \( i^{th} \) compartment from \( X_j \) infectious individuals; and \( V_i(X) \) is the net change of individuals in the \( i^{th} \) compartment by any other means. The rates are evaluated at the disease-free equilibrium, \( X^* \). The next generation matrix, \( K \), is then given by \( K = -FV^{-1} \). The \((i,j)\) element of the \( K \) matrix represents the number of secondary infected cases in compartment \( i \) produced by individuals in compartment \( j \). The basic reproduction number, \( R_0 \), is given by the spectral radius of the \( K \) matrix.

For our model, the transmission and transition matrices in the case with only cross-transmission between patients (\( F_P \) and \( V_P \), respectively) are given by:

\[
F_P = \begin{bmatrix}
\frac{U^* (1 - h)}{N} & \frac{U^* \beta (1 - h) \Omega_1}{N} & \frac{U^* \beta (1 - h) \Omega_2}{N} \\
\frac{U^*_A \beta \times 1.67 \times (1 - h)}{N} & \frac{U^*_A \beta \times 1.67 \times (1 - h) \Omega_1}{N} & \frac{U^*_A \beta \times 1.67 \times (1 - h) \Omega_2}{N} \\
0 & 0 & 0
\end{bmatrix};
\]

\[
V_P = \begin{bmatrix}
- (\gamma_C + \theta + \epsilon) & \lambda & 0 \\
\epsilon & - (\gamma_{CA} + \theta_A + \lambda) & (1 - \sigma) \tau + \eta \\
\theta & \theta_A & - (f + \tau + \eta)
\end{bmatrix}.
\]

The next generation matrix with only cross-transmission is then given by \( K_P = -F_P V_P^{-1} \).

The transmission and transition matrices in the case with only environment-patient transmission (\( F_E \) and \( V_E \), respectively) are given by:

\[
F_E = \begin{bmatrix}
\xi U^* (1 - h) \\
\xi U^*_A (1 - h) \\
0
\end{bmatrix}; \quad V_E = [-r \alpha].
\]

The next generation matrix with only environment-patient transmission, \( K_E \), is then given by

\[
K_E = F_E V_E^{-1} | \Phi_1, \Phi_2, \Phi_3 | V_P^{-1}.
\]

The next generation matrix of the model is then given by \( K = K_P + K_E \); and \( R_0 \) is given by the spectral radius of the \( K \) matrix. The high-dimension of the \( K \) matrix makes analytical solution for \( R_0 \) intractable. \( R_0 \) therefore was derived numerically in our model. Detailed discussion of the next generation matrix method for compartmental epidemic models can be found in Diekmann et al.\(^{38}\)
