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# A DYNAMIC PATIENT NETWORK MODEL OF HOSPITAL-ACQUIRED INFECTIONS

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## ABSTRACT

We investigate the transmission of infectious diseases in hospitals using a network-centric perspective. Patients who share a health care worker (HCW) are inherently connected to each other and those connections form a network through which transmission can occur. The structure of such networks can be a strong determinant of the extent and rate of transmission. We first examine how the density of the patient network affects transmission. Our experiments demonstrate that nurses are responsible for spreading more infection because they typically visit patients more often. However, doctors also pose a serious threat because their patient networks are more highly connected, which creates more opportunity for transmission to spread to multiple cohorts in the unit. We also explore the effects of patient sharing among HCWs, which temporarily alters the structure of the patient network. Our results suggest that this practice should be done in a structured manner to minimize additional transmission.

## 1 INTRODUCTION

The problem of hospital-acquired infections has been well-publicized and the best measures to control them have been studied extensively (Curtis 2008). However, research on this problem has not focused on the interactions among patients, nurses, and physicians. In general, we would like to maximize the number of healthcare workers (HCWs) who care for patients in a specific unit, but there are additional concerns. The underlying network of connections among the three types of actors involved and the nature of those interactions are also important factors. This paper presents results from a study of the network structure in a hospital unit and its effect on patient-to-patient transmission of infectious diseases.

With this model, we hope to accomplish two primary objectives. First, we want to model a network of patients in a hospital unit and the transmission of an infectious disease among the patients through the HCWs who care for them. The network structure plays an important role in transmission, and there may be observable trends related to the structure that are important to understand (Keeling 2005). Second, we want to investigate the effect of HCWs covering each other's patients temporarily and determine its effect on transmission. This practice is common in hospitals, but it is not well understood how it can change the dynamics of transmission. By focusing on these objectives, we gain a better understanding of how network structure affects transmission and we can offer strategies for staffing hospital units and sharing patients that are likely to minimize transmission.

## 2 METHODOLOGY

Agent-based modeling and simulation (ABMS) is a methodology that focuses on the interactions among individuals and aggregates that behavior into a system that can be analyzed (Macal and North 2007). Each individual agent can have different characteristics and behavior, which is an advantage of ABMS not afforded by equation-based modeling. Once a functional agent-based model has been developed, experiments are then conducted in which individual parameters are varied to determine their effect on the entire system. Our experiments focus on exploring the effect of network structure and patient sharing on transmission.

We developed our model of a patient network using NetLogo®4.0.4, an open source agent-based modeling development platform. In our model of a hospital unit, we explicitly define only patients as agents. Patients have a single, Boolean state that indicates whether or not the patient is infected or colonized with some type of pathogen. The two HCW types, nurses and physicians, are modeled implicitly through the transmission mechanism. Each patient has a primary nurse and a primary physician who provide care for that patient during the hospital stay. We control the proportion of visits performed by each HCW type because, in practice, nurses are likely to visit patients more often. Each time step, a random number is drawn to determine whether nurses or doctors will visit patients. All of the selected HCW type then visit a single patient in their respective cohorts.

As a consequence of HCWs caring for multiple patients, there is an underlying network that connects patients who share nurses and a separate network for patients who share physicians. Figure 1 highlights the difference between a dense network—one that has few HCWs and many connections between patients—and a sparse network. The patient network diagrams show 20 patients in a hospital unit with two physicians whose patients are indicated by the black and gray colors of the agents, respectively. The dense case on the left of Figure 1 shows how many connections exist in the nurse network when there are only two nurses, because the ten patients in each of the nurse cohorts are all connected. The sparse case shows the number of connections can be decreased significantly when there are ten nurses. The same comparison can be drawn for physicians.

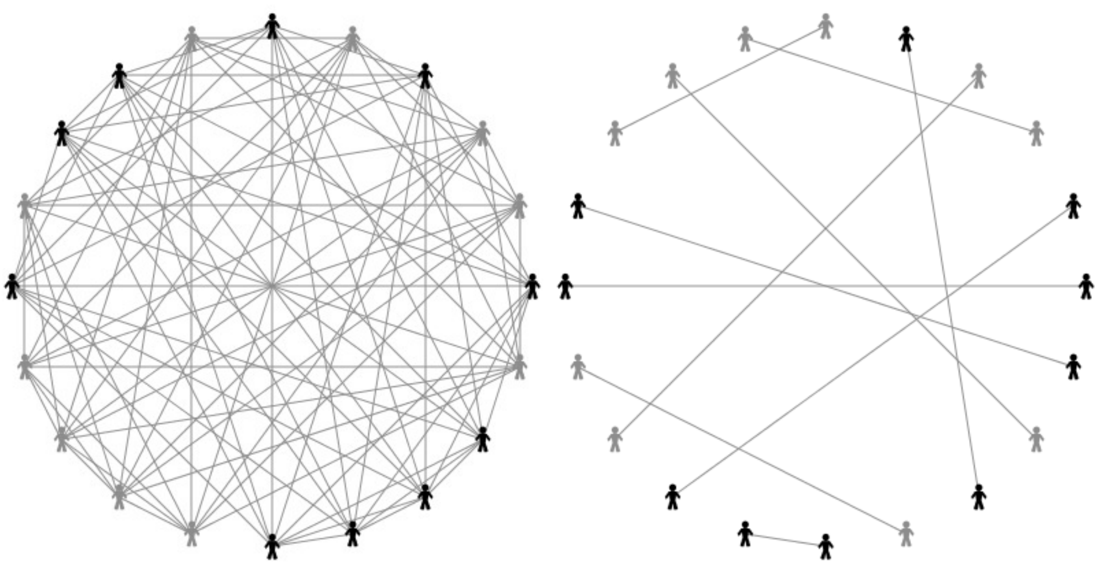

Figure 1: Example of a dense (left) and sparse (right) patient network. Patients that share a nurse are connected by a link while patients that share a physician have the same color.

Patients can only become infected if there is a source patient who shares a nurse or physician. Consequently, susceptibility implies there is a non-infected patient who has at least one connection to an infected patient at some point in time. Patients who are connected by a nurse and a physician have an increased likelihood of transmission if one of them becomes infected.

There is a single parameter, called *virulence*, which defines the probability of an infected agent transmitting the pathogen to a susceptible agent. Virulence takes into account a number of factors, including the probability of transmission between susceptible and infected agents, the probability that a HCW washes his or her hands, and the probability that the handwashing successfully removes the pathogen. This parameter can be adjusted to represent any number of changes in these factors. We can also vary the initial number of infected patients—which we call index patients—to determine their effect on the rate at which transmission occurs.

Patients can also be visited by secondary HCWs who may be covering the patient temporarily for the primary HCW. For example, this type of situation can occur in practice when HCWs are on lunch break or attending a meeting. We call these types of situations *patient sharing*, and will investigate various configurations by which this can be done in such a way that transmission is minimized. Patient sharing modifies the nurse and physician patient networks and creates temporary avenues for transmission to reach the rest of the unit. In our model, we set nurse and physician sharing rates that control how often the secondary HCW visits the patient, which creates a dynamic patient network—one in which connections not in the original network appear. Our goal is to understand how these temporary connections can affect the magnitude and rate of transmission in the unit.

We investigate four configurations of patient sharing, including the scenario in which no patients are shared. The patient sharing configurations are summarized in Figure 2. This figure shows four cohorts of patients and within each cohort, all of the patients are connected because they share the same HCW. With patient sharing introduced, temporary connections enter the network between patients in different cohorts, depending on the configuration of sharing. These cohort connections are bidirectional, because the secondary HCW can either introduce transmission into the new cohort or acquire the disease and bring it back to the primary patients.

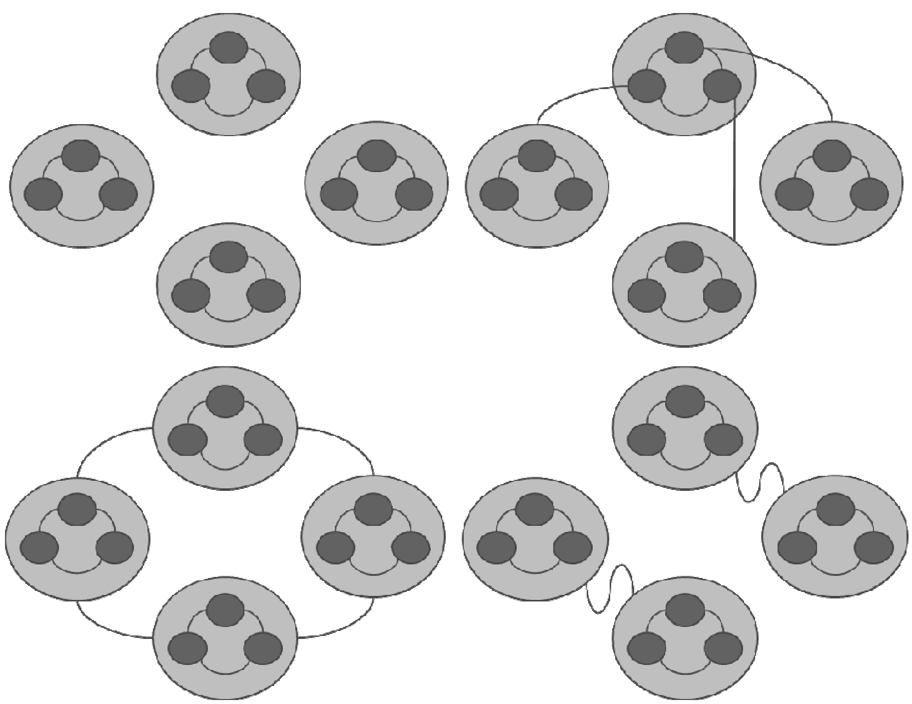

Figure 2: Patient sharing configurations (clockwise from top left: none, random, paired, and revolving)

The first type of sharing is *random sharing*, in which a HCW other than the primary care HCW is selected at random to visit the patient in need of care. This configuration of sharing creates a *small world effect* where patients can transmit infection to or become infected by patients who would not ordinarily share a connection (Watts and Strogatz 1998). The *paired sharing* configuration requires each HCW to have a partner who covers the primary patients. The HCW is also required to cover the partner's primary patients, creating pairs of HCWs that occasionally cover each others' patients. This configuration of sharing, although still creating additional links in the network, attempts to keep the network as disconnected as possible in order to limit transmission. *Revolving sharing* is the final patient sharing configuration. This configuration creates a circular network in which each HCW covers all of the patients of one HCW and is covered by a different HCW (e.g., HCW A covers for HCW B who covers for HCW C who covers for HCW A).

## 3 RESULTS

Our first series of experiments focuses on the transmission parameters and patient network structure. We restrict our experiments to a model of a 20-patient intensive care unit (ICU) in a hospital for the purpose of comparison. We first experiment with virulence to demonstrate its effect on transmission. For simplicity, we use a single nurse and no physicians in the ICU, essentially allowing all of the patients to mix. As our primary output, we use the mean number of ticks, an arbitrary NetLogo unit of time, over a specified number of Monte Carlo replications until all of the susceptible patients have become infected. In our model, ticks essentially equate to the amount of time between HCW visits to the patient, which depends on the number of patients, number of HCWs, number of visits each day, and the proportion of visits performed by each HCW type.

In some cases, not all patients will be susceptible to infection, as they may not have a connection to an infected patient. In such cases, the simulation ends once the last susceptible patient becomes infected. Consequently, it is important for us to track the total number of transmissions because the elapsed time until all patients become infected can be misleading. ABMS allows us to track the number of transmissions due to each HCW type so we can gain an understanding of the threat each poses to patients.

The effect of increasing virulence demonstrates a diminishing return, as shown in Figure 3, which matches the behavior we typically see with hand-hygiene compliance in other models (Barnes, Golden and Wasil 2010; Beggs, Shepherd, and Kerr 2008; McBryde, Pettitt, and McElwain 2007; Raboud et al. 2003). As virulence continues to increase, its effect on the speed at which transmission occurs decreases. However, when virulence drops below approximately 0.3, the time it takes for all of the patients to become infected grows significantly. For the remaining experiments, we fix virulence at 0.1, so that we can isolate the effects of the other experimental factors.

We investigate the effect of the number of index patients, those patients who are initially infected, on

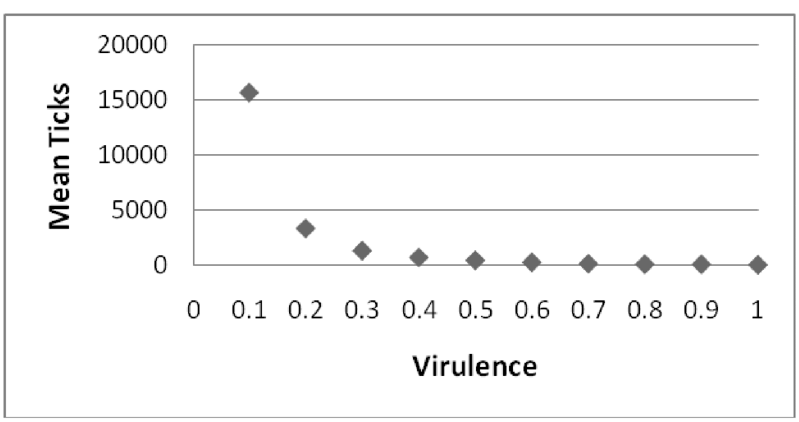


Figure 3: Mean time to infect all 20 patients as a function of virulence in an ICU with a single nurse

transmission. As shown in Figure 4, the effect of the number of index patients on transmission is approximately linear and does not appear to have any nonlinear effects. In the remaining experiments, we hold the number of index patients to a single patient for consistency.

Given the number of patients and HCWs, we can compute the density of the nurse and physician networks as the ratio of connections between patients to the number of links in the complete network where all patients are connected. For example, an ICU with 20 patients, 10 nurses, and 2 physicians would have 10 nurse cohorts of 2 patients each and 2 physician cohorts with 10 patients each. This is the sparse network scenario shown in Figure 1. For the nurse network, we would have 10 cohorts, each containing one connection between two patients. The physician network would have 2 cohorts, each containing 10 patients that are all connected. The total number of connections in each of these cohorts is 45 because each patient is connected to 9 neighbors and we divide by 2 to account for duplicate links. To compute the total number of connections possible, we use the total number of patients in the same way to arrive at 190. Dividing the number of nurse and physician connections by this value would yield a nurse network density of 0.0526 and a physician network density of 0.474. The nurse network density in the dense network scenario from Figure 1 is also 0.474. Equation 1 shows how to compute nurse and physician network density (d) for a unit with n total patients and k cohorts with $i_k$ patients each.

$$d = \frac{\sum_k \binom{i_k}{2}}{\binom{n}{2}} \tag{1}$$

The HCW network density varies according to the trend shown in Figure 5, which shows a diminishing change as the number of HCWs increases. This effect translates to a reduction in transmission, in both the number of patients susceptible to infection and the rate at which that transmission occurs. Network density is used as the independent variable for the remaining experiments in place of the number of HCWs to demonstrate its direct effect on transmission. A disadvantage of using network density in this manner is that it lacks resolution at larger values, but these values are not as likely to occur in practice. In addition, network density offers a normalized metric that can be used to compare units of different sizes and configurations. These types of comparisons are not always simple to perform using absolute parameters (e.g., the number of HCWs), and they become especially complex for units with non-uniform cohort sizes.

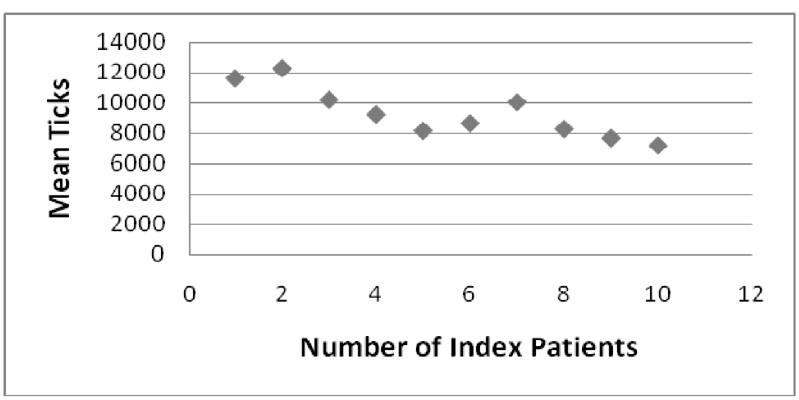


Figure 4: Mean time to infect all 20 patients as a function of the number of index patients in an ICU with a single nurse

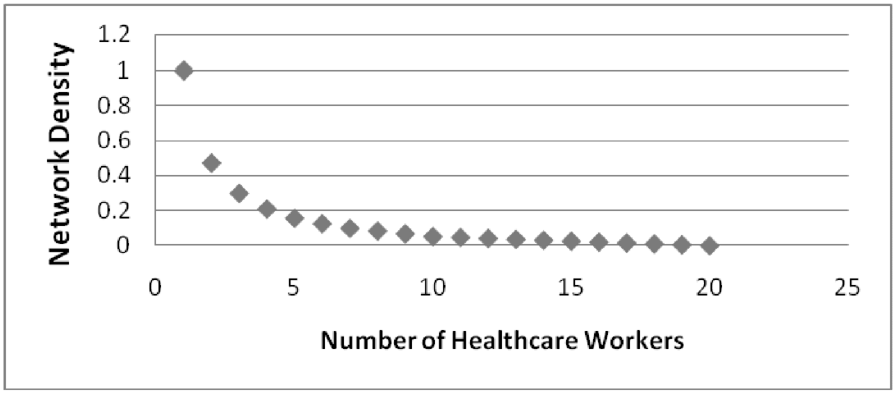


Figure 5: Health care worker network density as a function of the number of healthcare workers in a 20-patient ICU

We performed experiments in which we varied the nurse and physician network density to determine its effect on transmission. We configured the model to have nurses visit patients 80% of the time and the physicians visit patients the remaining 20%. The results show that our primary metric was not always useful for these experiments because of the dependence of the number of susceptible patients on network density and its subsequent effect on the time of the last infection. However, we can compute the ratio of mean ticks to the total number of transmissions in the unit to determine the mean time to infection in the unit. This response better represents the speed at which transmission occurred in the unit, and is a relevant metric regardless of the number of patients infected. Obviously, it is in the best interests of the patients to implement control measures that increase the mean time to infection as much as possible.

The effects of nurse and physician network density on our system are summarized in the following figures in the form of contour plots that shade areas from light to dark as the value of the response increases. The first plot shows the effect of network density on the mean time to infection and is shown in Figure 6. For example, at point A, we have nurse and physician densities of 0.474, which correspond to two nurses and two physicians in our 20-patient ICU. At this combination of nurse and physician density, the system responded with a mean time to infection of approximately 822 ticks, which is represented in the plot with a light gray color. At point B, we have a nurse density of 0.126 and a physician density of

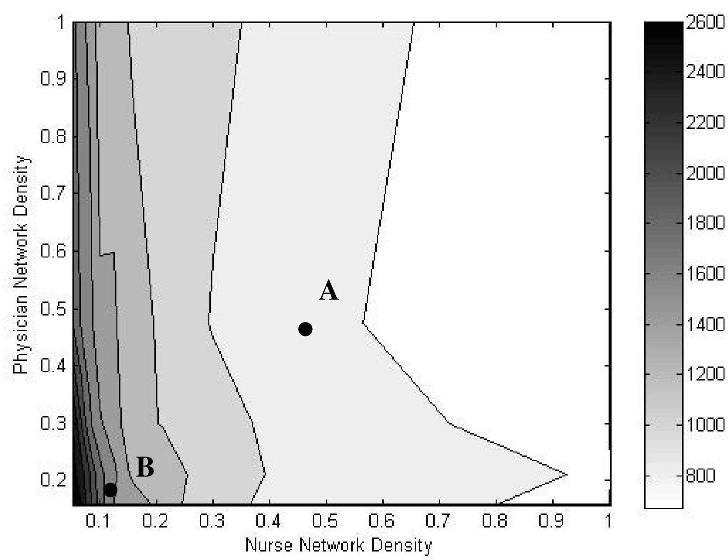


Figure 6: Mean time to infection as a function of nurse and physician network density

0.158, which is a much sparser network. As a result, the mean time to infection increases almost two fold to approximately 1600 ticks, which is represented on the plot by a darker shade.

It is clear from Figure 6 and Figure 7, which show contours for the number of transmissions due to nurses and physicians, that transmission is strongly correlated with the density of the nurse network. Highly dense nurse networks—density values of 0.3 and higher, which correspond to a nurse-to-patient ratio of 1:7 or less—are in danger of allowing transmission to reach the entire unit very quickly. Even moderately dense nurse networks—densities ranging from 0.1 to 0.3 (1:7 to 1:3 ratio) — put nurses in the position where they are likely to infect most of the unit. In order to minimize the amount of transmission and maximize the average time between transmissions, nurse network densities of 0.1 or less are required, which corresponds to an average nurse-to-patient ratio of 1:3 or better.

Despite the lower proportion of transmissions due to physicians, physicians still pose a significant threat in several ways. As shown in Figure 7, physician transmissions reach their highest point when the nurse network becomes very sparse. At these values, physicians begin to infect more patients because the nurses are no longer able to infect patients at such a fast rate. Physicians also pose a threat because their network can overlap multiple nurse networks. Therefore, physicians can transmit the infection from one nurse cohort to one or more others that would not have been affected by nurses, which is only possible when there is a HCW that visits many patients (Temime et al. 2009). Once the infection reaches this new cohort, nurses can then spread the infection to the rest of the patients. In effect, one physician transmission could turn into many additional transmissions down the road. Due to the important roles that both nurses and physicians play in transmission, maximizing the mean time to infection involves keeping both the nurse and physician densities at their lowest possible levels.

To demonstrate the threat physicians pose to patients, we repeat the same experiment and increase the rate at which physicians visited patients from 20% to 30%, thereby decreasing the rate of nurse visits to 70%. In an ICU environment, this rate of physician visits is still reasonable due to the severity of the condition of the patients. With the increased visit rate for physicians, we can see in Figure 8 that the highest mean time to transmission values requires lower physician network densities than in the original case. In addition, the highest mean times to transmission are lower than in the original case, suggesting that the additional physician visits are causing a faster transmission rate throughout the unit. Figure 9 shows that the number of transmissions due to each HCW is more balanced than in the previous experiment as well. These are significant changes in the response caused by a moderate change in the visit rate of physicians, further suggesting that physicians play a critical role in the transmission of infection.

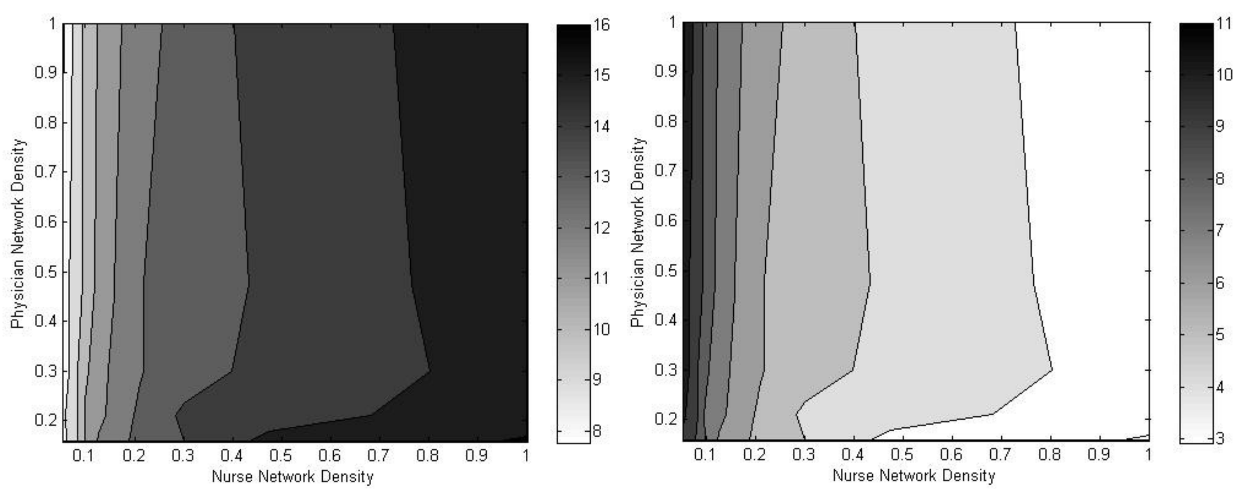


Figure 7: Transmissions due to nurses (left) and physicians (right) as a function of nurse and physician network density

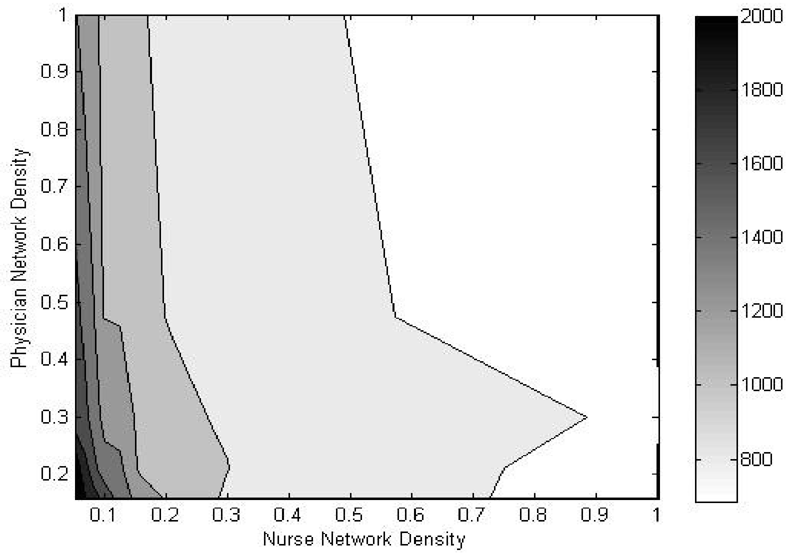


Figure 8: Mean time to infection as a function of nurse and physician network density with 70% nurse visit rate

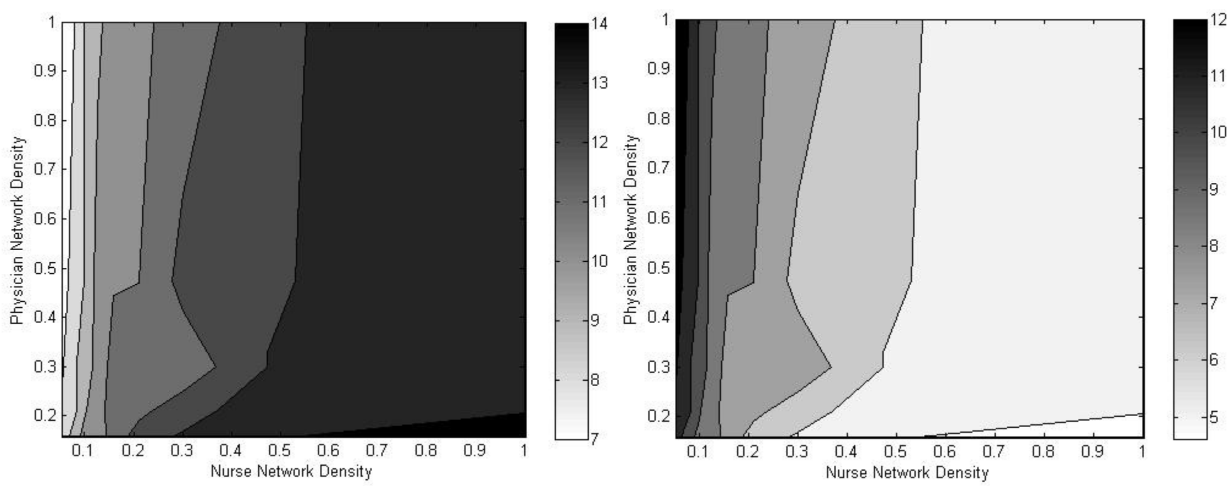


Figure 9: Transmissions due to nurses (left) and physicians (right) as a function of nurse and physician network density with 70% nurse visit rate

In almost all cases, every patient in the ICU eventually became infected. This full coverage was primarily due to the overlap of the nurse and physician networks. In an ICU with no physicians and a single index patient, we would only expect to see the patients who share a nurse with that index patient become infected. With this idea in mind, if we assign a number of nurses to a single physician who cares for all of the patients in the union of the nurse networks, then we essentially segment the patient population in the unit. In effect, this control measure minimizes the potential of physicians—who typically are fewer in number and, therefore, see more patients—to spread infection to patients to multiple nurse cohorts. We investigate the impact of this control measure on transmission.

For simplicity, we present the results in Figure 10 and Figure 11 as only a function of nurse network density averaged over all values of physician network density. The most important result of this experiment is highlighted in Figure 10. With the exception of a fully connected nurse network (i.e., one nurse

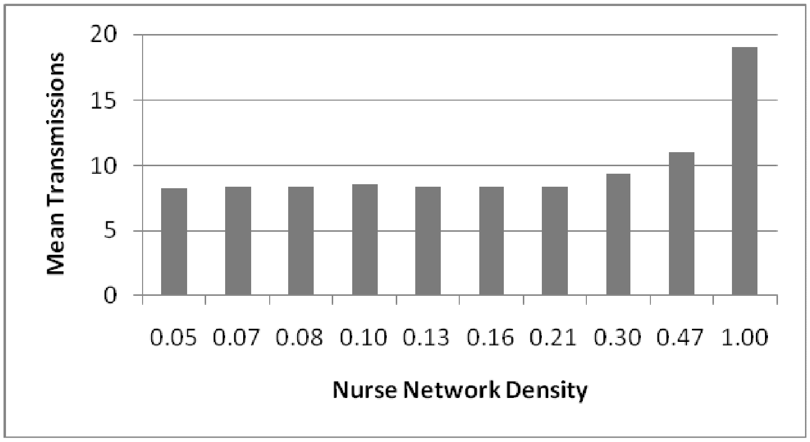


Figure 10: Mean number of transmissions as a function of nurse network density with aligned physicians

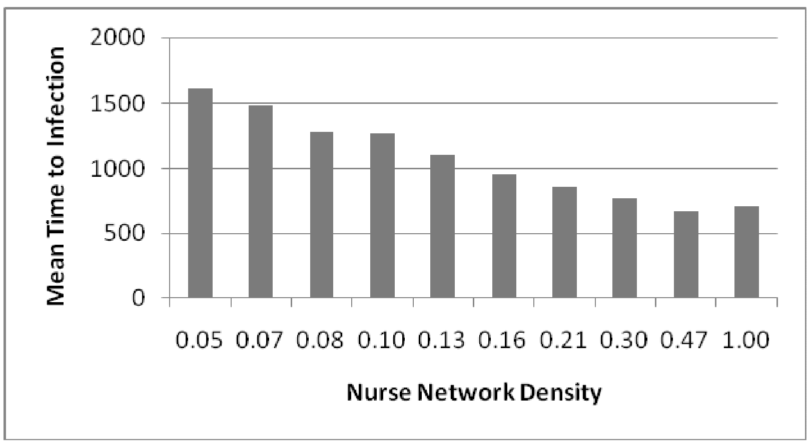


Figure 11: Mean time to infection as a function of nurse network density with aligned physicians

covering the entire unit), cohort alignment on average reduces the number of infected patients in the unit by approximately half, which essentially equates to the number of patients under the care of a single physician in this case. For units with additional physicians, this number is likely to be even lower. Even as the mean number of transmissions stabilizes, we continue to see an improvement in the mean time to infection as the nurse network density decreases, suggesting that cohort alignment could have a significant effect in an ICU environment.

We now move on to the second phase of experiments. These focus on the effect of patient sharing among HCWs in an ICU environment. These experiments use both HCW types, but only allow one type to share patients. This scenario mirrors a hospital in practice as nurses are likely to cover each others' patients more often than physicians. In addition, there are typically only a small number of physicians in each unit and patient sharing configurations begin to look the same. This fact is especially relevant for our simulated ICU where we have only two physicians, in which case random, revolving, and paired sharing all result in the same physicians covering each others' patients.

We simulated the same ICU using each sharing configuration for nurses and varying the patient sharing rate from 10% to 30% of patient visits. These results are summarized in Figure 12 and Figure 13. It is clear from the results that no sharing is the ideal configuration, resulting in the longest mean times to infection and the fewest number of transmissions due to nurses. The number of transmissions due to nurses is a good indicator of the vulnerability of the unit to transmission because nurses visit patients

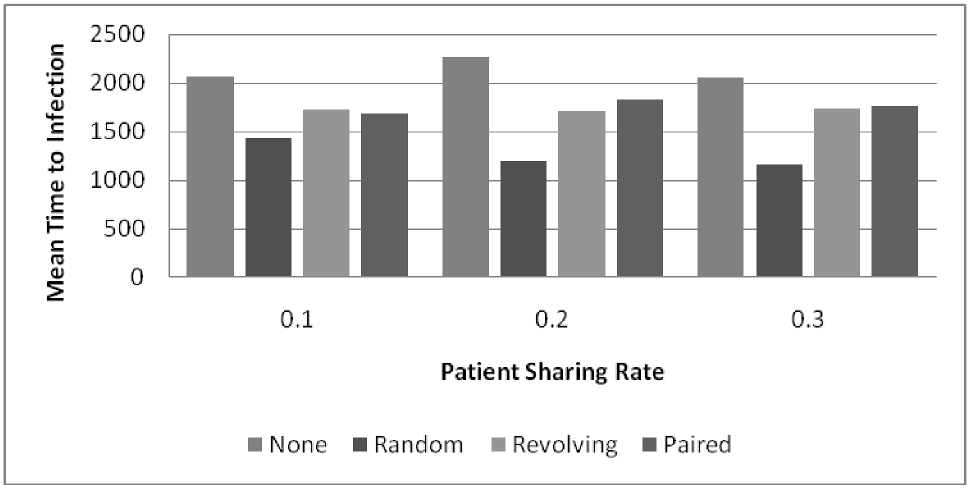


Figure 12: Mean time to infection as a function of sharing configuration and rate

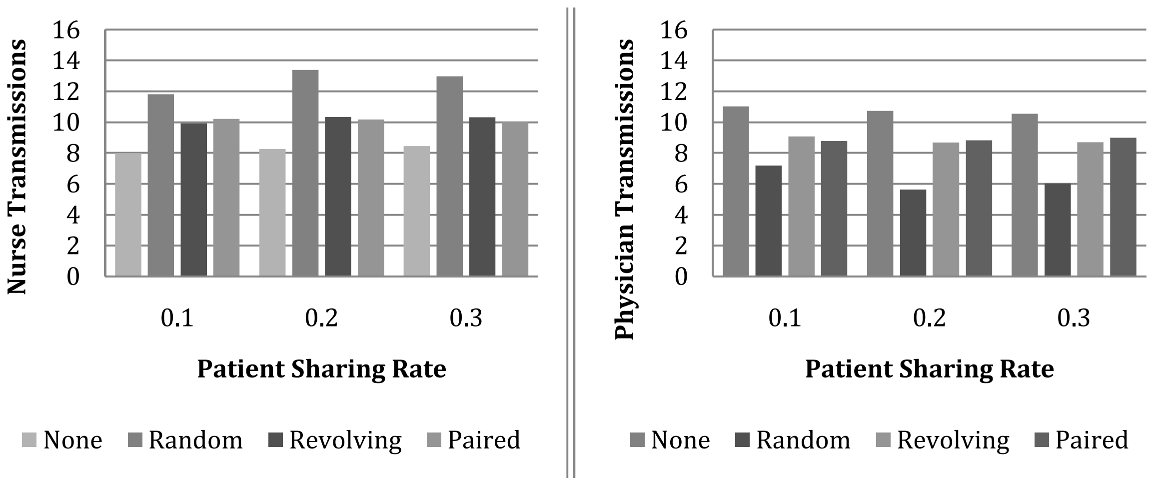


Figure 13: Nurse and physician transmission data as a function of sharing configuration and rate

more often than physicians. Consequently, cases where we see higher transmission numbers for physicians suggest that transmission is not occurring at a fast rate.

Another result is that the random sharing configuration is the worst of the sharing configurations, leading to the lowest mean times to infection and the highest transmission values by nurses. Random sharing allows transmission to occur between cohorts that would otherwise be disconnected in terms of the HCWs that care for those patients. Transmission in this 'small world' case creates multiple infection sources that can spread concurrently to neighboring cohorts in the unit.

The revolving and paired sharing configurations perform much better than random sharing, although it is not entirely clear which configuration is better. Revolving sharing attempts to maximize the time for infection to spread to the entire unit, whereas paired sharing attempts to restrict transmission to the two cohorts that share nurses. However, the physicians prevent both of these purposes from playing out because they can spread the infection to other nurse cohorts, which causes infection to spread faster and to patients who were not originally susceptible to infection.

In any case, it appears that at a 10% sharing rate, or low rates in general, revolving sharing performs slightly better, because transmission must occur along the circular path to reach the entire unit. However, at higher patient sharing rates, transmission is able to occur faster around the network and paired sharing becomes a better method, because the only path for infection to spread throughout the unit is through physicians. These trends are more pronounced when the ICU is simulated with only nurses.

## 4 CONCLUSIONS

We used an agent-based model to simulate the effect of network density and patient sharing on transmission in an ICU. By examining the density of the nurse and physician networks, we gained a new perspective of the effect of the implicit connections that exist among patients because they share a HCW. In addition, we gained a better understanding of the nonlinear effects that can be inflicted on the system through linear changes. For example, we expect a different level of transmission by increasing the number of nurses from 1 to 2 than we would by increasing the number of nurses from 4 to 5. In both cases, we added one nurse to the unit but the marginal benefit is greater in the former case. Our results showed that both nurses and physicians pose significant threats to patients in terms of infection, but they do so in different ways. Nurses can spread infection to patients quickly within their cohorts, but are limited in their ability to spread infection throughout the entire unit. Physicians spread infection much more slowly but their infections can accelerate transmission in the unit.

Our agent-based model also enabled us to investigate the effect of patient sharing, which is an important practical consideration that is often overlooked in epidemiological modeling. We learned that patient sharing has a negative effect on transmission, but revolving and paired sharing configurations present better alternatives to random sharing, which is most likely the way sharing is performed in practice. Physicians can negate the intended benefits of these configurations because of the extent of their networks, but they can still reduce the rate and incidence of transmission.

Agent-based modeling provides a convenient framework for simulating transmission in a hospital and can contribute valuable insight to professionals in infection control. In many cases, recommendations cannot be easily implemented because there are many practical considerations to take into account. However, modeling can provide insight into the dynamics of transmission that cannot be experimented with in practice, which allows hospital professionals to focus their resources on implementing actual changes to reduce transmission.

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