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Research article

A computational investigation of COVID-19 transmission inside hospital wards and associated costs

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Abstract: The COVID-19 pandemic has placed a particular burden on hospitals: from intra-hospital transmission of the infections to reduced admissions of non-COVID-19 patients. There are also high costs associated with the treatment of hospitalised COVID-19 patients, as well as reductions in revenues due to delayed and cancelled treatments. In this study we investigate computationally the transmission of COVID-19 inside a hospital ward that contains multiple-bed bays (with 4 or 6 beds) and multiple single-bed side rooms (that can accommodate the contacts of COVID-19-positive patients). The aim of this study is to investigate the role of 4-bed bays vs. 6-bed bays on the spread of infections and the hospital costs. We show that 4-bed bays are associated with lower infections only when we reduce the discharge time of some patients from 10 days to 5 days. This also leads to lower costs for the treatment of COVID-19 patients. In contrast, 6-bed bays are associated with reduced hospital waiting lists (especially when there are also multiple side rooms available to accommodate the contacts of COVID-19-positive patients identified inside the 6-bed bays).

Keywords: COVID-19; hospital transmission; multiple-bed bays; multiple bay wards; hospital costs; computational model; numerical predictions

1. Introduction

The current coronavirus disease 2019 (COVID-19) pandemics has placed a great burden on hospitals, leading not only to reduced hospital admissions and delayed treatments for a variety of patients [1] but also causing increased hospital transmission of this disease among the hospitalised patients (i.e., nosocomial infections) [2]. This is a particularly concerning aspect in the context of new SARS-CoV-2 variants (e.g., the Omicron variant) that are more transmissible than the original variants [3].

In the context of COVID-19 hospital transmission, a recent study [4] showed that hospital patients are much more likely to be infected by other patients than by health-care workers (HCW). In particular, 21% of patients (super-spreaders) can cause up to 80% of infections [4]. This is important since most UK hospitals have to accommodate patients in multiple-bed bays: 6-bed bays or 4-bed bays [5, 6]. There are also single-bed rooms (called side rooms) [5], but these are not enough to accommodate all patients.

In multiple-bed bays across various Scottish hospitals, the distance between beds is not always greater than 2 m, to reduce the transmission of the SARS-CoV-2 infection. This aspect is complicated by the fact that these viral particles can have various sizes [7] (i.e., within the droplet range, > 10 μm; as well as within the aerosol range, < 10 μm) and therefore they can have dual transmission: droplet-like transmission (at distances < 2 m) and airborne-like transmission (across distances > 2 m). Thus, if an exposed patient is admitted to hospital in a multiple-bed bay, after the incubation period the patient can transmit the disease to the neighbouring beds. To address this issue, some recent studies investigated the use of partition screens in multi-bed bays to reduce the transmission of infection [8]. However, since partition screens are not the standard approach in many Scottish hospitals, we will ignore them in this study.

Hospitals need to make decisions regarding the distribution of patients inside bays, to ensure that as many as possible patients are treated, while avoiding the transmission of COVID-19 among patients in multiple-bed bays. To this end, NHS produced a standard operating procedure on guidance for hospitalised patients with confirmed or possible COVID-19 infections [6]. According to this guidance, any new positive COVID-19 cases have to be isolated either in a single room or in a multiple-bed bay in a COVID-19-only area, while the contacts of a new positive COVID-19 case in a multiple-bed bay should be isolated or cohorted together in wards that are combinations of single rooms and bay areas.

The main goal of this study is to investigate which type of hospital bay distribution produces the most/least COVID-19-infected patients and most/least patients on the waiting list (i.e., patients not admitted to the hospital due to a lack of available beds). However, at the same time, we want to ensure that this type of investigation can be generalised and applied also to other infectious diseases that are transmitted across hospital wards (i.e., not only aerosol-transmitted pathogens such as SARS-CoV-2 [7] or *Mycobacterium tuberculosis* [9] but also droplet-transmitted pathogens such SARS-CoV-2[7] and *Bordetella pertussis* [9]). To this end, we consider a computational approach using a generalisation of a network model introduced in [10] to simulate the dynamics of a hospital ward that contains multiple-bed bays as well as single rooms. We investigate two scenarios: (i) every hospital bay containing an exposed individual that can infect his or her neighbours, which then need to be isolated in side rooms – if available – thus putting pressure on new hospital admissions; (ii) only one bay in the ward containing an exposed individual but with an infection that could be spread to other bays due to healthcare staff or contaminated surfaces (eventually leading again to pressure on new hospi-

tal admissions). Moreover, since at the beginning of the pandemic, it was thought that SARS-CoV-2 was transmitted through droplets, and now this perspective has changed towards an aerosol-dominated transmission [11] (although, as shown in [7], SARS-CoV-2 viral particles can have sizes < 10 μm as well as sizes > 10 μm), we also investigate the impact of the assumptions of pathogen transmission within a 2 m - distance (i.e., for droplet-transmitted diseases) vs. pathogen transmission at distances much greater than 2 m (i.e., for aerosol-transmitted diseases). In addition, we investigate the role of isolation period (10 or 14 days) on the number of infections and number of patients on the waiting list, as well as the impact of a probability of patient discharge after 5 days.

The novelty of this study lies in (i) the generalisation of the approach in reference [10] to a whole hospital ward (formed of multiple-bed bays and single rooms, which allow for the isolation of infected patients discovered in multiple-bed bays), (ii) the investigation of the transmission of the infectious disease at short ranges (< 2 m) and long ranges (> 2 m) and (iii) the consideration of the costs of hospital stays, to see if there is a trade-off between the costs of COVID-19 treatments vs. the costs of treatments for patients that could not be admitted to the hospital (since all beds are blocked by COVID-19 contacts).

2. Materials and methods

2.1. Model description

In this study we model computationally the transmission of COVID-19 among patients inside a hospital ward that contains either 4-bed bays or 6-bed bays, as well as single-bed rooms. The model used is an extension of a model used in [10] to investigate the spread of COVID-19 inside one 4-bed bay versus one 6-bed bay. More precisely, the model is an individual-based network model that tracks susceptible, exposed, infected and recovered patients. For each patient $P_{n,t}$ (with $n = 1...N$, the number of patients in the ward) the model tracks at each time t various individual characteristics: the epidemiological status (susceptible, exposed, infected or recovered), the bay/side room in which the patient is placed, the bed in which the patient is placed inside a bay/side room (see also Figure 1), the start of the incubation period, the duration of the incubation period, the time since the individual has become infectious, and the recovery time; for details see [10]. To update numerically the epidemiological status, note that a susceptible patient may become exposed with probability β after an interaction with an infected patient, where β depends on the distance d_{ij} between a susceptible and an infected patient. In this study we investigate two different forms of this probability $\beta(d_{ij})$: (a) $\beta(d_{ij}) = \exp{-\frac{3}{2}d_{ij}}$ (which assumes droplet-based transmission of pathogen; see Figure 2, Table 1 and also [10]) and (b) $\beta(d_{ij}) = \exp{-\frac{1}{3}d_{ij}}$ (which assumes aerosol-based transmission of pathogen; see Figure 2 and Table 1). Note also that in a 6-bed bay the distance between 2 beds is less than 2 m, while in a 4-bed bay this distance is larger than 2 m (which influences the transmission probability β); see also Figure 1. Moreover, if a patient is exposed to the viral infection, then the incubation time is increased by Δt at each iteration, until the patient becomes infectious. Likewise, the infection time is increased by Δt until the patient recovers. The duration of the incubation stage is described by an Erlang distribution with mean $1/\sigma$ and shape 2. The duration of the recovery stage is described by an Erlang distribution with mean $1/\gamma$ and shape 2. The parameters used in this model (with their values) are summarised in Table 1. For a more technical description of the computational model, see [10].

As opposed to the study in [10], which focused only on the transmission of SARS-CoV-2 inside a
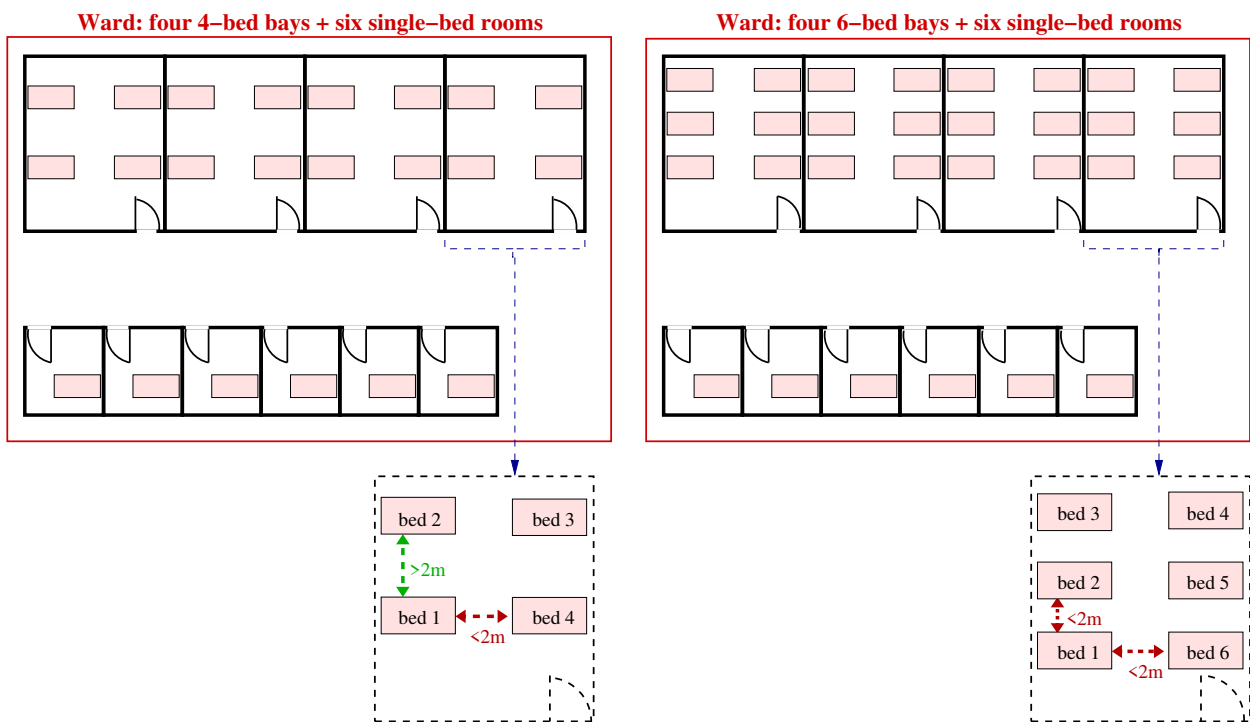
Figure 1. Description of the two types of hospital wards that we consider in this computational study: a ward consisting of four 4-bed bays and six single rooms (left) and a ward consisting of four 6-bed bays and six single-bed rooms. In the zoomed-in bays, we show in red the distance between beds that is less than 2 m, and in green the distance between beds greater than 2 m.
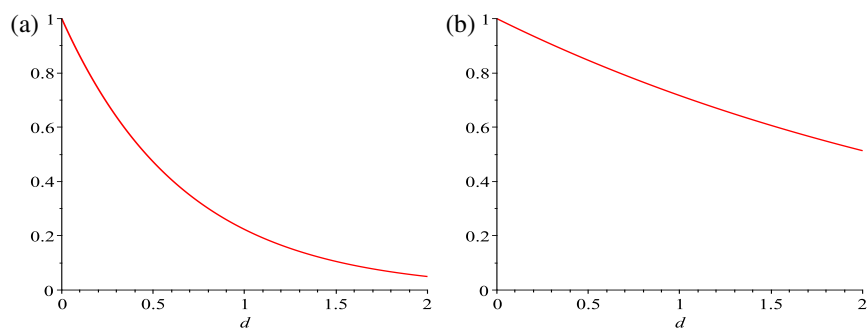
Figure 2. Description of the transmission probability $\beta(d_{ij})$ as a function of the distance d_{ij} between infected and susceptible patients: (a) $\beta(d_{ij}) = \exp -\frac{3}{2}d_{ij}$, (b) $\beta(d_{ij}) = \exp -\frac{1}{3}d_{ij}$. The vertical axis shows only distances $d_{ij} \in [0, 2]$ m, since the literature suggested that a 2 m distance should be enough for avoiding infection in the case of droplet-based transmission (sub-panel (a)). In sub-panel (b) we show that in the case of airborne-based transmission, when $d_{ij} = 2$ there is still a very large probability of disease transmission.

single bay (and only within a 2 m spatial distance from the infected individual), here we focus on a whole hospital ward formed of four patient bays with six additional single-bed rooms (known as side rooms); see also Figure 1. This leads to new population dynamics inside the ward, which is investigated in this study to better understand the role of COVID-19 transmission inside the whole ward:

- To imitate real hospital regulations, if a patient is identified as COVID-19-positive, it is moved to a COVID-19-only ward, and its contacts are moved to available side rooms. We close a hospital bay if we cannot transfer all of the COVID-19 exposed individuals out of it, due to lack of available side rooms. This bay will remain closed for the duration of the isolation period (described by parameter δ and defined as the time a patient is separated from others after contacting the disease) to allow for the patients inside the bay to recover. Conversely, the bay will remain open if we are able to move all of the contacts of a COVID-19-confirmed patient to available side rooms. Throughout this study we assume a maximum isolation period for COVID-19 patients of $\delta = 14$ days, based on [6, 12]. We also investigate the effects of an isolation period of $\delta = 10$ days, based on the latest WHO criteria for releasing patients from isolation [12].
- To account for the fact that not all patients stay in the hospital for an extended period of time (e.g., due to the type of their medical treatment, or due to patients being discharged quickly, with or against medical advice) we implement a probability factor (τ) which dictates whether a patient will leave the hospital bay or the side rooms after 5 days. We assume here that the average stay in the hospital is 5 days, based on data in references [13, 14].
- Additionally, we have used real hospital data to derive a daily infection rate α due to nosocomial transmission (i.e., contact with infected doctors, nurses, toilets, etc.) and to predict a realistic influx of patients that will enter the hospital at the beginning of each day; for details see Section 2.2 below. Whenever we are unable to move the influx of new patients into a hospital bay (because it is already occupied), they are put onto a waiting list. By doing so, we are able to track both the number of patients that become infected and the number of patients who fail to be admitted to the hospital due to a lack of space throughout the cycle.

With these assumptions we can compare which bay size produces the most/least infected patients and most/least waiting patients.

2.2. Parameter estimation

The parameters used for our numerical simulations are summarised in Table 1. Most values are taken directly from the literature (see the last column in Table 1). Note here the difference between α, which is the daily infection rate due to patients' contact with infected healthcare workers or infected surfaces, and β, which is the probability that a susceptible patient will contract COVID-19 from other infected patients in the same bay (as given by the distance d_{ij} between two beds i and j inside a 4-bed or a 6-bed bay; see Figure 1 for beds, placement inside bays and [10] for a discussion of distances between beds).

In the following, we discuss in more detail how we estimate the patient influx into the hospital ward, as well as the hospital infection rate using anonymised patient data from Ninewells Hospital in Dundee, UK. We also discuss in more detail how we approximate the mean hospital stay length.

- *Patient influx.* Using anonymised patients admission data during the pandemic time (January 2021, see Figure 3(a)), we tried to identify which probability distribution (uniform, exponential,

Table 1. Summary of model parameters, together with their values used for the numerical simulations.

Parameter	Description (unit)	Value	Reference
$1/\sigma$	Mean incubation period (days)	5.2	[15, 16, 17, 10]
σ	Incubation rate (1/day)	0.1923	[15, 16, 17, 10]
$1/\gamma$	Mean recovery/infection period (days)	7	[18, 10, 19]
γ	Recovery rate (1/day)	0.1428	[18, 10, 19]
β	Probability of infection $= \exp(-\frac{3}{2}d_{ij})$ or $= \exp(-\frac{1}{3}d_{ij})$, with d_{ij} = distance between beds i and j in meters	(0,1)	[10]
α	Daily infection rate (1/day)	0.1389	estimated
δ	Isolation period (days)	10, 14	[6, 12]
τ	Probability of discharge after 5 days (%)	10, 20, 50	[13, 14]

Poisson, normal) describes best the frequency of admissions. Our results showed that the best fit was given by an exponential distribution with a rate of 0.3 (see Figure 3(b)).
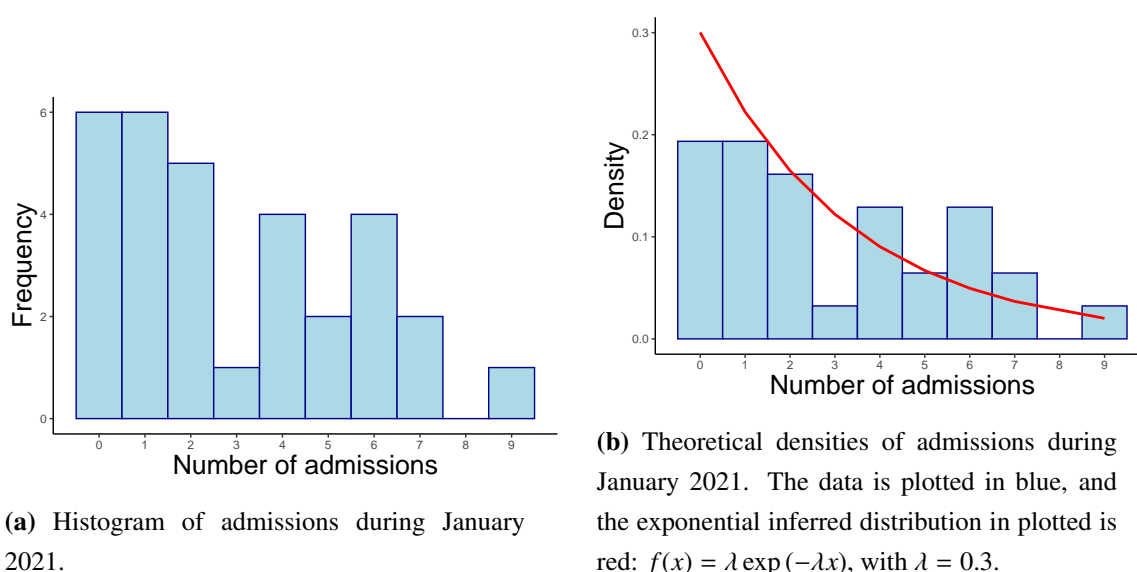

(a) Histogram of admissions during January 2021.

(b) Theoretical densities of admissions during January 2021. The data is plotted in blue, and the exponential inferred distribution in plotted is red: $f(x) = \lambda \exp(-\lambda x)$, with $\lambda = 0.3$.

Figure 3. Distribution of admissions during January 2021, using anonymised data from Ninewells Hospital in Dundee, UK.

- *Infection rate.* To estimate the intra-hospital infection rate, we used the data on the number of hospital discharges per day (in January 2021). Then, we minimised the least-square difference between hospital discharge data and the hospital discharges obtained through numerical simulations, i.e., $\min F(\alpha) = \min \|discharge_{data} - discharge(\alpha)\|$, where α is the infection rate (see Figure 4). For each value of the infection rate, we computed the least square difference $M = 200$ times in order to liaise with the inherent randomness of the model. Then, we plotted this dif-

ference (i.e., $f(\alpha) = \frac{1}{M} \sum_{m=1}^{M} F_m(\alpha)$, where $F_m(\alpha)$ is the difference in one run of the algorithm) in Figure 4, where we showed a succession of zoom-ins of $f(\alpha)$ for narrower values of α. The minimum value of $f(\alpha)$ was achieved when $\alpha = 0.1389^*$, which we selected as the infection rate for this study.
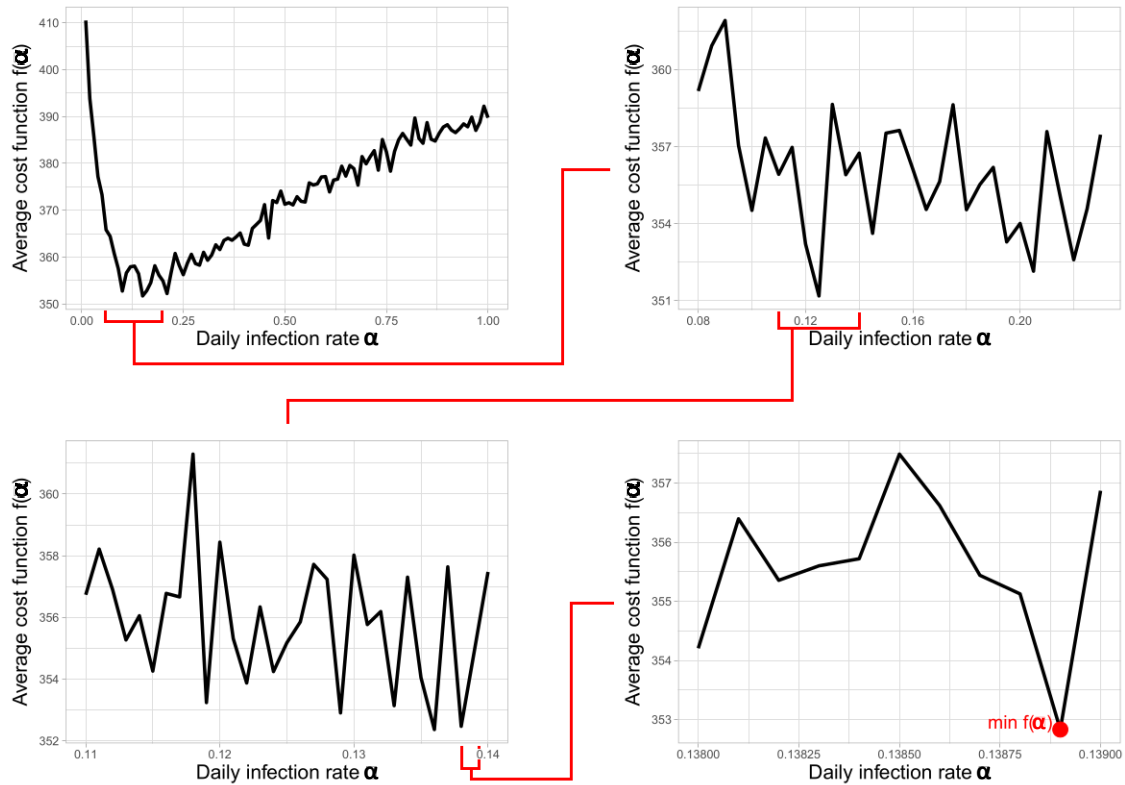

Figure 4. Succession of zoom-ins of $f(\alpha)$ for narrower values of α.

- *Mean hospital stay length.* In [13], the authors have overviewed the mean length of hospital stay in England for 10 different types of treatment (in non-COVID-19 years). These stay lengths ranged from 0.7 days for hernia to 20.2 days for stroke. If we would average all these treatments, we would obtain an average stay of 7.12 days (in England). However, in Scotland, the priority was to reduce the time patients spend in the hospital (to reduce also the risk of healthcare-acquired infections) [14]. Thus, the data in [14] shows that the average length of stay across all NHS boards was 4.3 days. Throughout this study we assumed an average length of hospital stay of 5 days, and after those days there would be a probability that the patient is discharged.

3. Results

For the numerical simulations presented here, we fix $1/\gamma = 7$ days, $1/\sigma = 5.2$ days, and we run the simulations up to $T_{max} = 31$ days. We run this network model 500 times, and we compute the

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*We note that this minimum could have been obtained using different other approaches that involve data smoothing and/or function fitting to the data followed by the identification of the minimum of that function.

means and standard deviations of these 500 runs for individuals in each epidemiological state (i.e., susceptible, exposed, infected, recovered), for each of the 4-bed or 6-bed bays. We already mentioned before that the probability of infection β is given by a decaying exponential, which depends on the distance between beds (see also Table 1).

Finally, as initial conditions for these simulations, we assume that all patients are susceptible, with the exception of

(i) *1 exposed individual in each bay* (so 4 exposed individuals per ward). In this case we want to investigate the redistribution of contact patients across the ward, and its effect on the waiting list for hospitalisation.

(ii) *1 exposed individual in one random single bay* (so 1 exposed individual per ward). In this case we want to investigate the spread of infection across the ward (due to the nosocomial infection rate α).

For simplicity and to be able to compare the outcomes of various simulations, we arbitrarily chose to place the exposed individual in bed 2 (see Figure 1).

3.1. 1 bay

We begin by taking a look at the most basic form of our model (also discussed in [10]): one bay holding either 4 or 6 beds without any side rooms. This case will serve as a baseline for comparison with the situations discussed in the next sub-sections, where we will focus on the whole hospital ward. Moreover, we investigate the effect of disease spread at short range, < 2 m (corresponding to droplet-like transmission, as shown in Figure 2(a)) versus disease spread over much longer ranges, > 2 m (corresponding to airborne-like transmission; as shown in Figure 2(b)).

In Figure 5 we see that having 6-bed bays leads to a larger number of infected COVID-19 patients (almost twice as many patients as compared to the 4-bed bays; see left sub-panels). The number of patients on the waiting list is slightly higher for the 4-bed bays compared to the 6-bed bays. Moreover, by comparing panels (a),(b) (droplet-like transmission) with panels (c),(d) (airborne-like transmission), we see that, as expected, there are more infected patients when the viral particles can travel distances greater than 2 m. However, the number of patients on the waiting list does not change.

3.2. 4 bays

Next, we investigate what happens when we increase the number of patient bays to four. In doing so, the model becomes more realistic, as it attempts to emulate a hospital ward. For this simulation we altered the isolation period parameter by first setting it to 10 days (see Figure 6(a),(b)) and then to 14 days (see Figure 6(c),(d)). For a 10-day isolation period we see that having more bays leads to a slightly lower number of individuals on the waiting list compared to the 1-bay case above. Moreover, there are more infected individuals in the 6-bed bay as opposed to the 4-bed bay, and more patients on the waiting list for the 6-bed bay compared to the 4-bed bay. Increasing the isolation period to 14 days (Figure 6(c),(d)) does not seem to have a significant impact on the number of infected patients (although there seem to be slightly lower patient numbers when $\delta = 14$ days), but it leads to an increase in the number of patients on the waiting list.
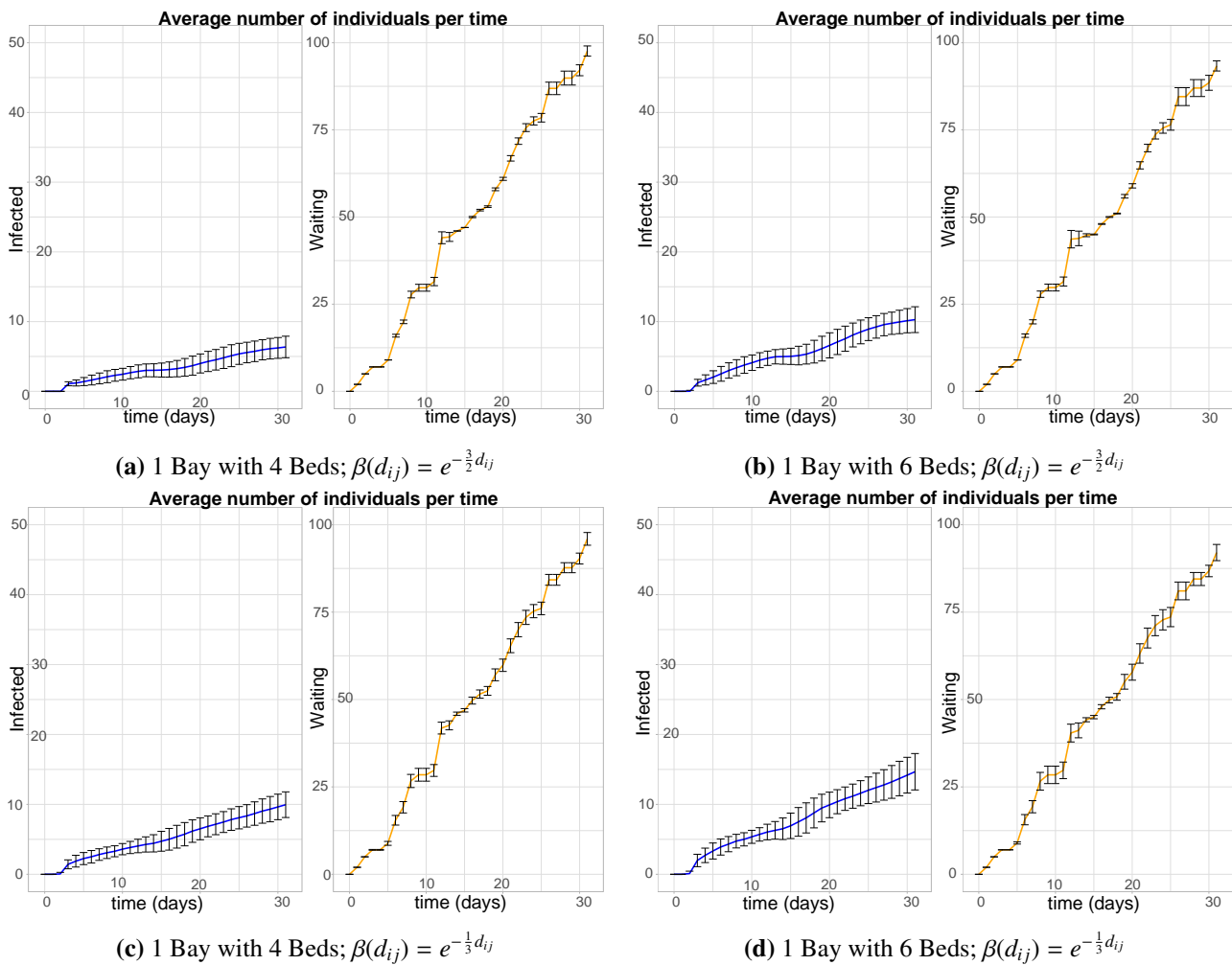
Figure 5. Model dynamics for the case of 1 bay with either (a) 4 beds or (b) 6 beds. Panels (a),(b) consider the transmission probability $\beta(d_{ij}) = \exp\left(-\frac{3}{2}d_{ij}\right)$, while panels (c),(d) consider the transmission probability $\beta(d_{ij}) = \exp\left(-\frac{1}{3}d_{ij}\right)$. Here we assume that the isolation period is $\delta = 10$ days, we close the bay if we encounter an infected patient, and the daily infection rate is $\alpha = 0.1389$.

3.3. 4 bays + 6 side rooms

To account for hospitals that contain single-bed rooms (used for patients who have been exposed to a pathogen), next we implement the situation where close contacts of an infected patient are moved to these side rooms. We assume that the isolation period is set to $\delta = 10$ days. For this most general case we also investigate the assumption of short-range (< 2 m) versus long-range (> 2 m) disease spread. In this case we also discuss two initial conditions:

- *Initial conditions (i): 1 exposed individual in each bay (i.e., 4 exposed individuals across the whole ward).* We see in Figure 7 that including also the 6 side rooms decreases the number of
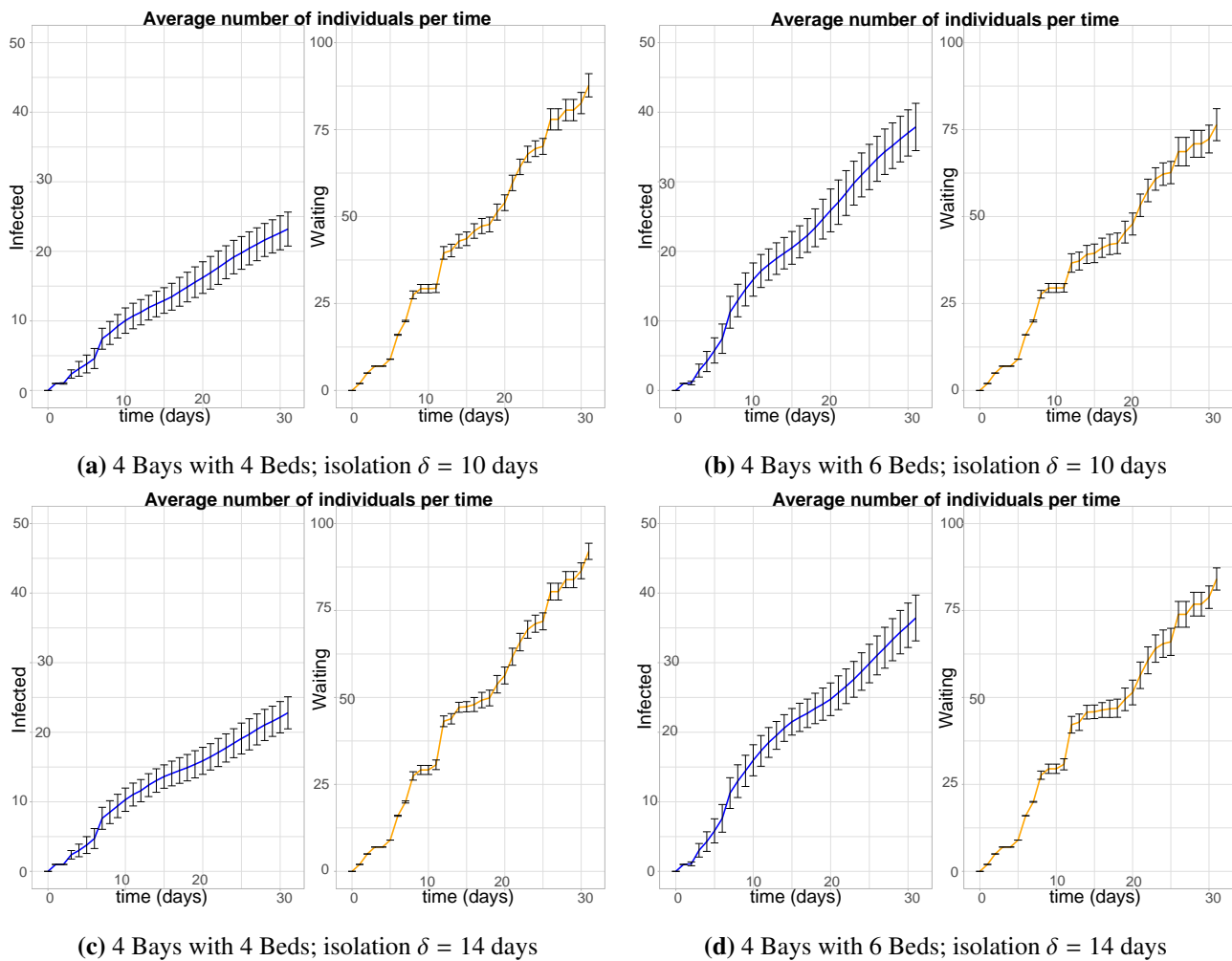
(a) 4 Bays with 4 Beds; isolation $\delta = 10$ days

(b) 4 Bays with 6 Beds; isolation $\delta = 10$ days

(c) 4 Bays with 4 Beds; isolation $\delta = 14$ days

(d) 4 Bays with 6 Beds; isolation $\delta = 14$ days

Figure 6. Model dynamics when the ward contains only 4 bays (no side rooms) with either (a),(c) 4 beds or (b),(d) 6 beds. We also investigate the impact of isolation period: (a),(b) $\delta = 10$ days, and (c),(d) $\delta = 14$ days. Here we assume that $\beta(d_{ij}) = \exp(-\frac{3}{2}d_{ij})$. The initial conditions are (i): one exposed individual in each bay of the ward (i.e., 4 exposed patients per ward, at initial time).

infected patients in 6-bed bays (from ≈ 37 patients on day 30 for 6-bed bays, to ≈ 33 patients on day 30 for 6-bed bays + 6 side rooms). There is no significant change for the 4-bed bays. Moreover, the waiting time is also slightly reduced on day 30 for all types of bays. Moreover, as expected, the assumption that the disease can spread to distances > 2 m leads to larger numbers of infected patients, but relatively similar numbers of patients on the waiting lists.

• *Initial conditions (ii): 1 exposed individual in one single random bay (i.e, 1 exposed individual per ward).* In Figure 8 we see that there are no significant differences in the numbers of infected patients and patients on the waiting list between Figures 7 and 8. Therefore, the different initial conditions do not seem to impact the dynamics of the ward system. As before, the type of disease
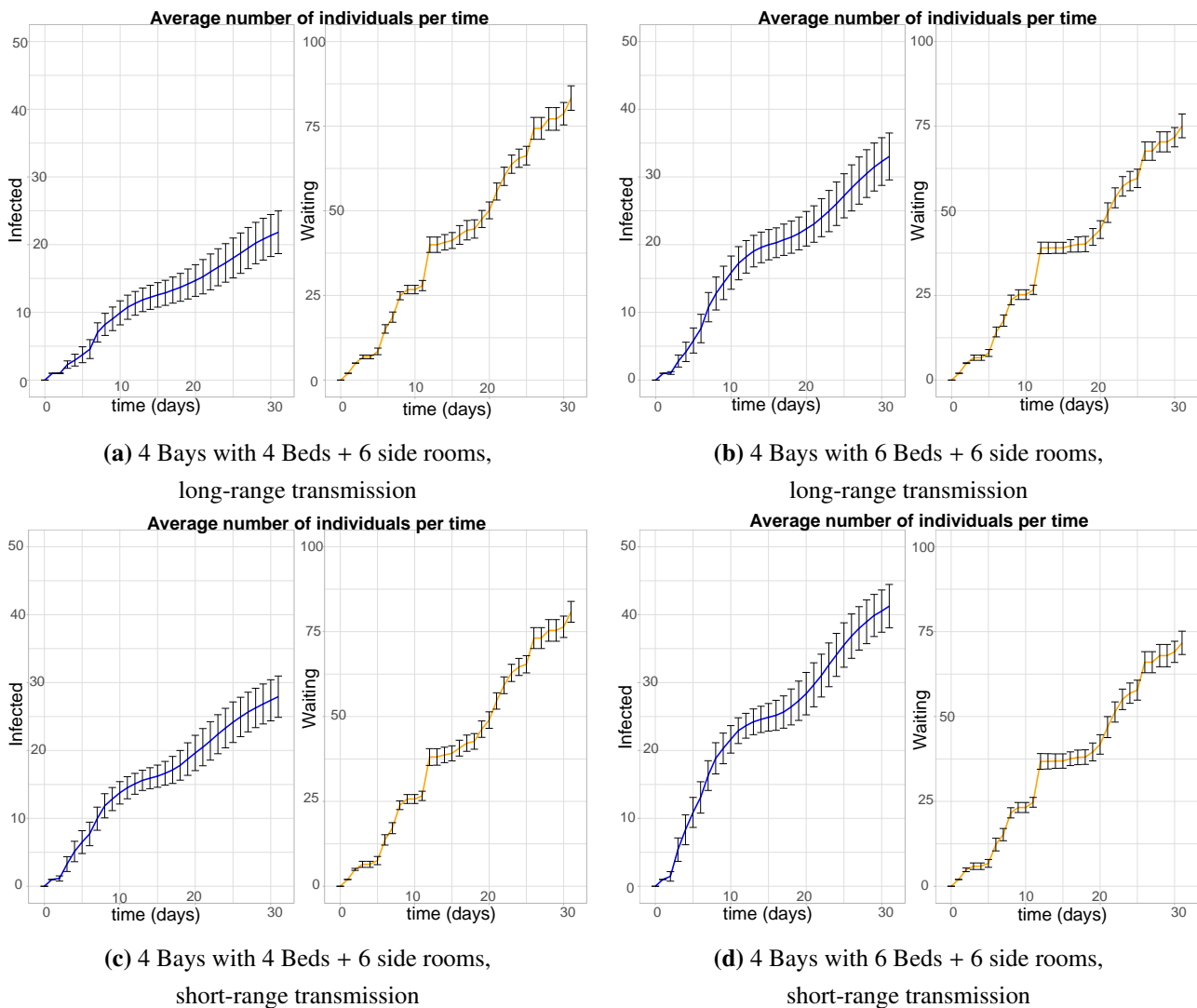
Figure 7. Model dynamics for the case of 4 bays + 6 side rooms, with either (a),(c) 4 bed-bays or (b),(d) 6 bed-bays. We assume that *1 exposed individual can be found in each single bay* (so 4 exposed individuals per ward). Panels (a),(b) consider the transmission probability $\beta(d_{ij}) = \exp\left(-\frac{3}{2}d_{ij}\right)$, while panels (c),(d) consider the transmission probability $\beta(d_{ij}) = \exp\left(-\frac{1}{3}d_{ij}\right)$. Moreover, we assume that the isolation period is $\delta = 10$ days. We close the bay(s) if we encounter an infected patient, and the daily infection rate is $\alpha = 0.1389$.

transmission, i.e., short-range (< 2 m) versus long-range (> 2 m), impacts the number of infected patients per ward (with more infected patients if the probability of disease spread at larger distances is very high). Because of these expected results, in the following sections we will ignore the type of transmission probability, and focus only on the case $\beta(d_{ij}) = \exp(-\frac{3}{2}d_{ij})$ (as in [10]).
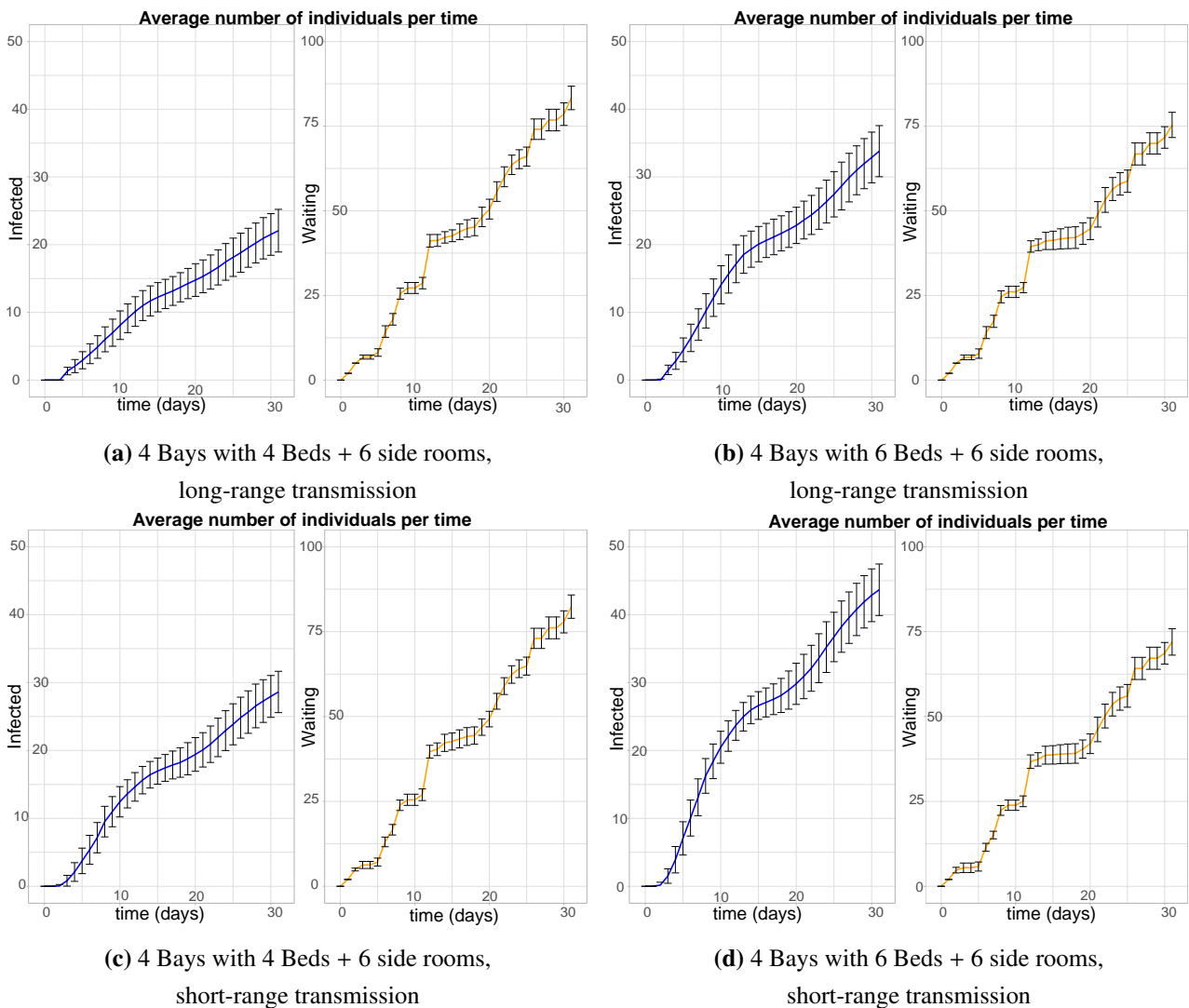
Figure 8. Model dynamics for the case of 4 bays + 6 side rooms, with either (a),(c) 4 bed-bays or (b),(d) 6 bed-bays. We assume that *1 exposed individual can be found in one single random bay* (i.e., 1 exposed per ward). Panels (a),(b) consider the transmission probability $\beta(d_{ij}) = \exp\left(-\frac{3}{2}d_{ij}\right)$, while panels (c),(d) consider the transmission probability $\beta(d_{ij}) = \exp\left(-\frac{1}{3}d_{ij}\right)$. Moreover, we assume that the isolation period is $\delta = 10$ days. We close the bay(s) if we encounter an infected patient(s), and the daily infection rate is $\alpha = 0.1389$.

3.4. 4 bays + 6 side rooms + probability of patients leaving after 5 days

In an attempt to add another layer of realism to the model, we implement a probability factor in which there is a chance that a patient can leave the bay or side rooms after 5 days of hospitalisation (as discussed in Section 2.2, based on the NHS data). Here, we consider a 20% probability of this happening. If a patient is not discharged on day 5, there is a 20% probability of being discharged on

day 6, and so on. In Figure 9 we consider again the initial condition (i) with 4 exposed individuals per ward, and see that discharging patients earlier leads to a decrease in the number of patients on the waiting list (as expected). This decrease is very strong for the 6-bed bays. However, unexpectedly, this early discharge also leads to a strong increase in the number of infected patients across all types of bays. We will discuss this result in more detail in Section 5.
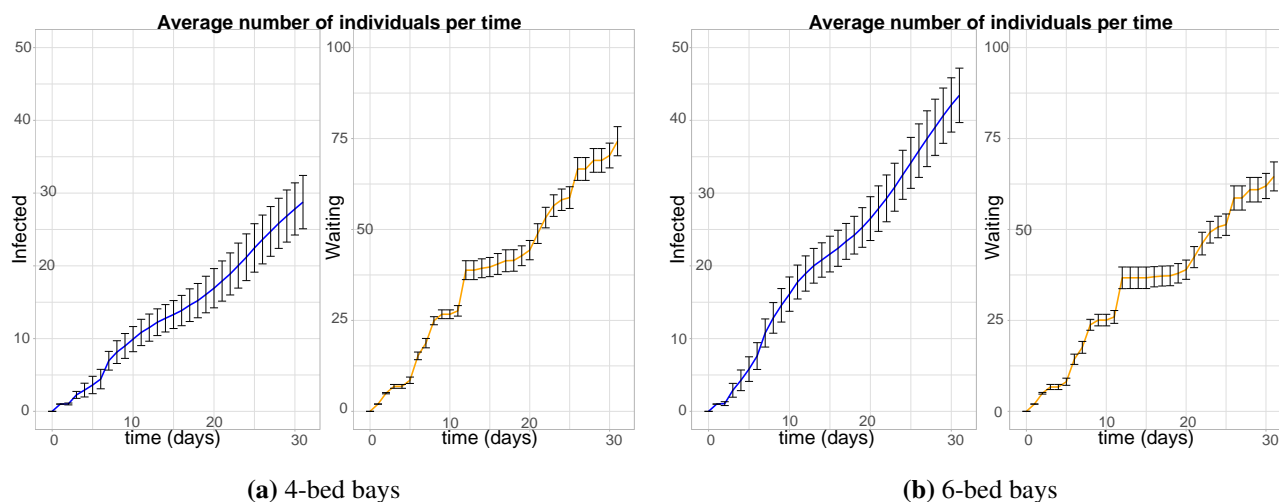

Figure 9. Model dynamics for the case of 4 bays + 6 side rooms, with either (a) 4 beds or (b) 6 beds. The probability of a patient leaving after 5 days is 20%. The initial condition is (i) 4 exposed individuals, one in each bay. We assume that the isolation period is $\delta = 10$ days, we close the bay(s) if we encounter an infected patients, and the daily infection rate is 0.1389.

Consider now the initial condition (ii), where only one exposed individual is hospitalised in one single random bay. In Figure 10 we observe that this condition does not lead to a significant change in the number of infected individuals, or the number of patients on the waiting list.

4. The costs of general hospitalisation vs. COVID-19 treatments

While the UK National Health Services (NHS) are free at the point of use for the patient, the system is taxpayer funded [20], and there are costs paid to NHS providers for delivering activity by key service areas [21]. Therefore, having patients on the waiting lists does have long-term health impacts for the patients (who cannot be treated immediately), as well as financial impacts for the hospitals, since patients with more serious medical problems (not treated on time) incur higher treatment costs.

In the following we investigate the costs of COVID-19 treatments for hospital-infected patients vs. the costs of not admitting patients to the hospital due to a lack of available beds (and thus a reduction in hospitals, revenues due to cancelled services).

4.1. Hospitalisation costs for COVID-19 patients

Here we focus on the case discussed in Figure 9 for 4 bays (6 beds in each bay), 6 side-rooms, and 20% probability of leaving after 5 days, and any day thereafter. We calculate the average hospitalisation
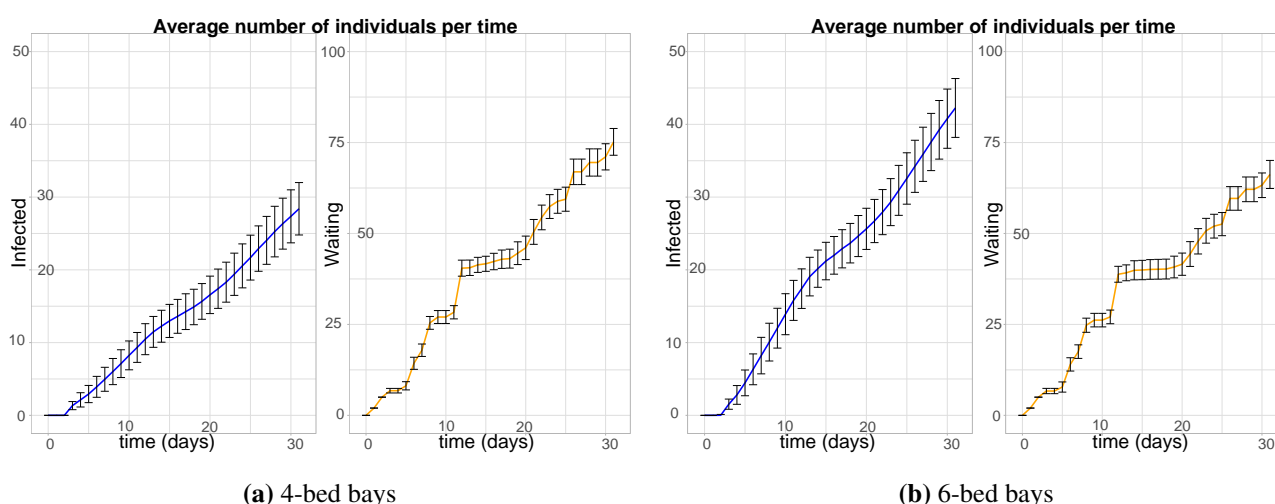
Figure 10. Model dynamics for the case of 4 bays + 6 side rooms, with either (a) 4 beds or (b) 6 beds. The probability of a patient leaving after 5 days is 20%. The initial condition is (ii) 1 exposed individual, in one single random bay. We assume that the isolation period is $\delta = 10$ days, we close the bay(s) if we encounter an infected patients, and the daily infection rate is 0.1389.

costs for COVID-19 patients by multiplying the number of infected patients per simulation by £2161, the UK hospital stay costs estimated in reference [22] (see the Appendix data of this study). Figure 11 shows the costs for the average number of infected patients (continuous curve) and its lower and upper boundaries (dashed curves) as given by one standard deviation above and below the mean value. The left sub-panels show the patient costs when the wards contain 4-bed bays (here costs reach an average of £60,000 after 30 days), while the right sub-panels show the patient costs when the wards contain 6-bed bays (here costs reach an average of £90,000 after 30 days). It is clear that having 6-bed bays leads to increased costs associated with the infected patients.

4.2. Costs associated with cancelled interventions (for patients on waiting lists)

To calculate the average amount that a hospital would lose due to patients being unable to be admitted (since these amounts would have otherwise been covered by patients' medical insurances), we first need to compute the average cost per non-COVID-19 admission. To this end, we used the data in Table 2 of the paper [13] (corresponding to the costs of 10 different medical treatments) to compute the average cost of stay per patient, which is £3016.3, with a standard deviation of £2071.9. This allows us to define an interval for the costs: £(3016.3 ± 2071.9). For the plots in Figure 12, we take the product of this interval with the average number of patients on the waiting list for the plots in Figure 9 (and obtain the continuous curves). The dotted lines represent data one standard deviation above and one standard deviation below the mean value. On day 30, the patients on the waiting list for wards with 4-bed bays would be associated with costs/revenues of $\approx$ £230,000, while the patients on the waiting lists for wards with 6-bed bays would be associated with costs/revenues of $\approx$ £200,000.
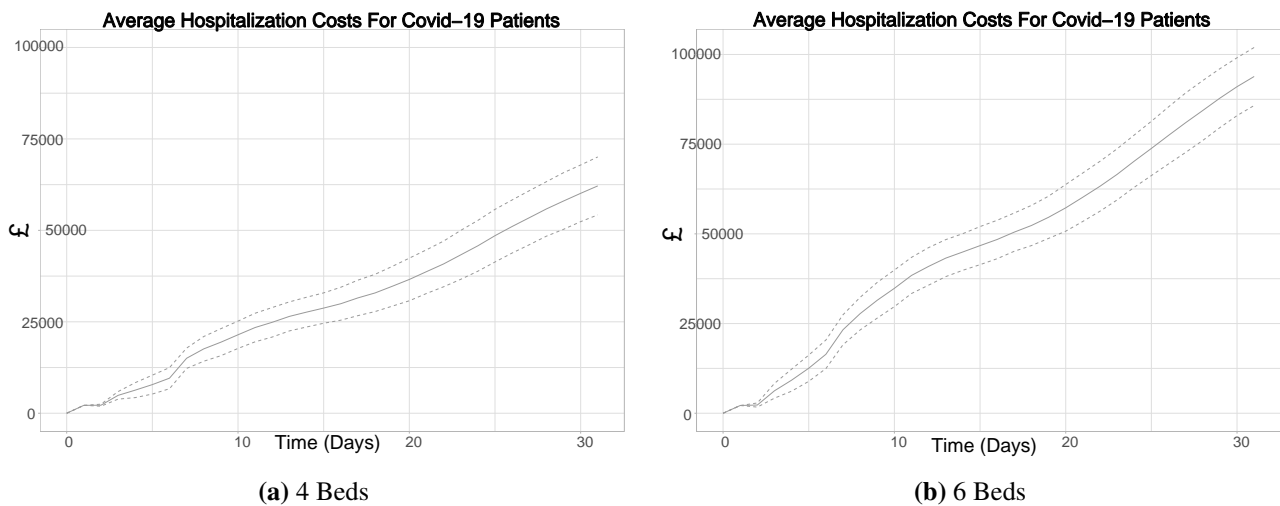
(a) 4 Beds

(b) 6 Beds

Figure 11. Hospital stay costs for patients hospitalised in wards that include (a) 4-bed bays + 6 side rooms, (b) 6-bed bays + 6 side rooms. We assume that the probability that the patients are being discharged from the hospital after 5 days is 20%. These costs correspond to the patients dynamics shown in Figure 9.

(a) 4 Beds

(b) 6 Beds

Figure 12. Costs associated with patients on the waiting lists which, if admitted to (a) 4-bed bays + 6 side rooms, or to (b) 6-bed bays + 6 side rooms, would have undergone various medical treatments that would have brought revenues to the hospitals (from patients' medical insurances). For the simulations we assume that the isolation period is $\delta = 10$ days, and the probability that the patients are being discharged from the hospital after 5 days is 20%. These costs correspond to the patients dynamics shown in Figure 9.
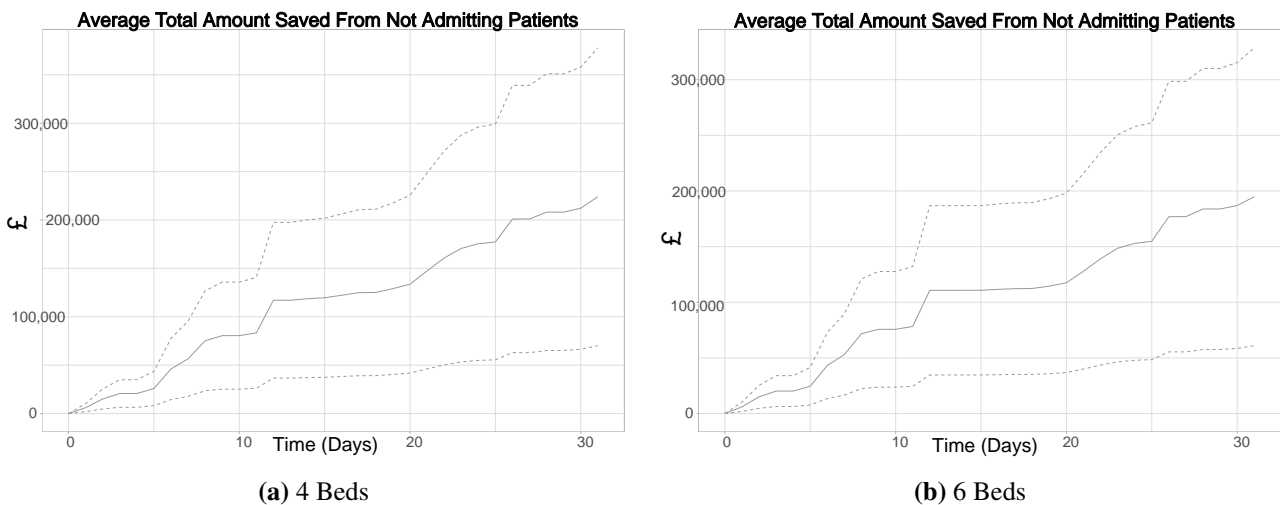
5. Discussion

In this study we used a computational approach (i.e., simulations of an individual-based network model) to investigate the impact of COVID-19 transmission among the patients in a hospital ward formed of 4-bed bays or 6-bed bays, in addition to side rooms that can be used to isolate the contacts of COVID-19-positive patients.

We showed that, compared to the case of a single bay (Figure 5 in this paper, also discussed in reference [10]), focusing on a complete hospital ward with multiple bays and side rooms leads to a more complex situation due to (a) the closure of bays in case of COVID-19 patients and a lack of side rooms to isolate all contacts and (b) the transmission of infection between different bays, and between bays and single rooms. More precisely,

- The increase in the isolation period of infected patients (from 10 days to 14 days) leads, as expected, to an increase in the number of patients on the waiting list (Figure 6). This increase was sharper for 4-bed bays compared to 6-bed bays.
- The addition of 6 side rooms might lead to a slight decrease in the number of infected individuals in 6-bed bays, and a slight decrease in the number of patients on the waiting list for 4-bed bays (compare Figure 6(a) with Figures 7 and 8). Note that the waiting lists are slightly longer for the case of 6-bed bays compared to the 4-bed bays.
- The different initial conditions, with (i) 4 exposed individuals in the ward vs. (ii) 1 exposed individual in the ward, do not have any significant impact on the number of infected patients or the number of patients on the waiting list. This suggests that the spread of infection does not depend on the number of exposed patients but rather on the presence of such an exposed patient.
- Unexpectedly, the discharge of patients after 5 days leads to an increase in the number of infected patients (and, a decrease in the number of patients on the waiting list, as expected); see Figures 9 and 10. This could be explained by the fact that the early discharge of hospitalised patients led to new patients being admitted, who can become infected due to the presence of an intra-hospital infection rate.

Impact of prevention measures. Note that this study does not consider directly the impact of measures used to reduce viral spread, such as mask wearing or ward ventilation [11]. These aspects are modelled indirectly through the different forms of the transmission rates (β). In fact, a change from the transmission rate depicted in Figure 2(b) to a transmission rate depicted in Figure 2(a) could be obtained under the assumption that hospitalised patients are continuously wearing masks. A more direct approach to model these aspects, for example by varying parameters describing the daily infection rate, or by varying the transmission rate throughout the day (since patients can wear masks only during some periods in the day), is not the subject of the current study and will be considered in future works.

In this study we also investigated the effect of an early patient discharge (i.e., on day 5, with 20% probability of discharge) and observed that an early discharge led to an unexpected increase in the number of infected patients across all types of bays. This is probably caused by the higher turnover of patients following early discharge, which leads to more patients becoming admitted to the hospital and becoming infected. Therefore, a reduction in the length of hospital stay might not lead to a reduction in the number of infections if the disease is very transmissible (as is the case of COVID-19), and if

no other reduction measures are implemented (e.g., ventilation, air filtration, use of high-grade masks whenever indoors [11]).

6. Conclusions

This theoretical study allows us to conclude that hospital wards with 4-bed bays might be better at reducing hospital transmission of infectious diseases. This could lead also to lower hospital costs (for the treatment of infected individuals). The patients on the waiting lists that do not get admitted to the hospital, are also associated with a loss of hospital revenues, which are slightly higher for wards with 4-bed bays versus wards with 6-bed bays.

Overall, these theoretical results suggest that by reducing the number of beds in a bay, the hospitals could eventually save money in the long term. However, for the validation of this model, we require more financial data related to patients hospitalisation costs, as well as data on the number of infected patients in specific hospital wards (which is not easily available).

To conclude, we mention that this study focused only on pathogen transmission based on distance, and this was the result of two aspects considered here. First, many hospital bays are quite small and the distance between beds cannot be always greater than 2 m, which impacts significantly pathogen transmission (via droplets or aerosols). Second, while other factors such as air movement, pathogen load, time spent by susceptible patients in the room, are also important (especially for aerosol transmission over larger distances), they might not be relevant for the particular case investigated here (i.e., COVID-19 spread across a hospital ward, in January 2021). For example, a very recent study [23] on aerodynamic analysis of hospital ventilation in winter/summer and its impact on COVID-19 transmission suggested that during winter, airborne spread of SARS-CoV-2 might be limited to hospital rooms, which was in contrast to summer airborne spread that could include also pathogen spread towards public areas and nurses' office. Regarding the time spent by susceptible patients in a room with an exposed patient, we note that this might not be easily changed due to patient treatment protocols and/or hospital rules. Nevertheless, we acknowledge the importance of such other factors that control aerosol transmission of pathogen at larger distances. The probability of infection due to other factors was implicitly considered here through a small probability (5%) that patients could become infected each day (see also [10]). To address this potential limitation, an explicit consideration of the role of other factors on pathogen transmission (especially aerosol transmission at distances > 2 m) will be the subject of future studies.

Conflict of interest

The authors declare no conflict of interest.

References

1. E. Rennert-May, J. Leal, N. X. Thanh, E. Lang, S. Dowling, B. Manns, et al., The impact of COVID-19 on hospital admissions and emergency department visits: A population-based study, *PLoS ONE*, **16** (2021), e0252441. https://doi.org/10.1371/journal.pone.0252441

2. Q. Du, D. Zhang, W. Hu, X. Li, Q. Xia, T. Wen, et al., Nosocomial infection of COVID-

19: A new challenge for healthcare professionals (review), *Int. J. Mol. Med.*, **47** (2021), 31. https://doi.org/10.3892/ijmm.2021.4864

3. I. Torjesen, COVID-19: Omicron may be more transmissible than other variants and partly resistant to existing vaccines, scientists fear, *Br. Med. J.*, **375** (2021), n2943. https://doi.org/10.1136/bmj.n2943

4. C. J. R. Illingworth, W. L. Hamilton, B. Warne, M. Routledge, A. Popay, C. Jackson, et al., Superspreaders drive the largest outbreaks of hospital onset COVID-19 infections, *eLife*, **10** (2021), e67308. https://doi.org/10.7554/eLife.67308

5. G. Moore, H. Rickard, D. Stevenson, P. Aranega-Bou, J. Pitman, A. Crook, et al., Detection of SARS-CoV-2 within the healthcare environment: A multi-centre study conducted during the first wave of the COVID-19 outbreak in England, *J. Hos. Infect.*, **108** (2021), 189–196. https://doi.org/10.1016/j.jhin.2020.11.024

6. *NHS Greater Glasgow and Clyde Control of Infection Committee*, Standard Operating Procedure (SOP): Pathways and cohorting guidance for patients with confirmed or possible COVID-19 or those who require shielding, 2020. Available from: https://www.cem.scot.nhs.uk/cvd/covcoh.pdf.

7. M. I. Guzman, An overview of the effect of bioaerosol size in coronavirus disease 2019 transmission, *Int J. Health Plann Mgmt.*, **36** (2021), 257–266. https://doi.org/10.1002/hpm.3095

8. C. M. Rooney, J. McIntyre, L. Ritchie, M. H. Wilcox, Evidence review of physical distancing and partition screens to reduce healthcare acquired SARS-CoV-2, *Infect. Prev. Pract.*, **3** (2021), 100144. https://doi.org/10.1016/j.infpip.2021.100144

9. *Centers for Disease Control and Prevention*, Review of scientific data regarding transmission of infectious agents in healthcare settings. Available from: https://www.cdc.gov/infectioncontrol/guidelines/isolation/scientific-review.html.

10. D. Moreno Martos, B. J. Parcell, R. Eftimie, Modelling the transmission of infectious diseases inside hospital bays: implications for COVID-19, *Math. Biosci. Eng.*, **17** (2020), 8084–8104. https://doi.org/10.3934/mbe.2020410

11. T. Greenhalgh, J. L. Jimenez, K. A. Prather, Z. Tufekci, D. Fisman, R. Schooley, Ten scientific reasons in support of airborne transmission of SARS-CoV-2, *Lancet*, **397** (2021), 1603–1605. https://doi.org/10.1016/S0140-6736(21)00869-2

12. *World Health Organisation*, Criteria for releasing COVID-19 patients from isolation, Scientific Brief, 2020. Available from: https://www.who.int/news-room/commentaries/detail/criteria-for-releasing-covid-19-patients-from-isolation.

13. J. Gaughan, A. Mason, A. Street, P. Ward, English hospitals can improve their use of resources: an analysis of costs and length of stay for ten treatments, *CHE Res. Paper 78*, 2012.

14. Public Health Scotland: Inpatient and Day Case Activity. Available from: https://www.isdscotland.org/health-topics/hospital-care/inpatient-and-day-case-activity.

15. M. Alene, L. Yismaw, M. A. Assemie, D. B. Ketema, W. Gietaneh, T. Y. Birhan, Serial interval and incubation period of COVID-19: a systematic review and meta-analysis, *BMC Infect. Dis.*, **21** (2021), 257. https://doi.org/10.1186/s12879-021-05950-x

16. C. Cheng, D. Zhang, D. Dang, J. Geng, P, Zhu, M. Yuan, et al., The incubation period of COVID-19: a global meta-analysis of 53 studies and a Chinese observation study of 11 545 patients, *Infect. Dis. Poverty*, **10** (2021), 119. https://doi.org/10.1186/s40249-021-00901-9

17. S. A. Lauer, K. H. Grantz, Q. Bi, F. K. Jones, Q. Zheng, H. R. Meredith, et al., The incubation period of coronavirus disease 2019 (COVID-19) from publicly reported confirmed cases: Estimation and application, *Ann. Int. Med.*, **172** (2020), 577-582. https://doi.org/10.7326/M20-0504

18. N. George, N. K. Tyagi, J. B. Prasad, COVID-19 pandemic and its average recovery time in Indian states, *Clin. Epidemiol. Glob. Health*, **11** (2021), 100740. https://doi.org/10.1016/j.cegh.2021.100740

19. R. F. Reis, B. de Melo Quintela, J. de Oliveira Campos, J. M. Gomes, B. M. Rocha, M. Lobosco, et al., Characterisation of the COVID-19 pandemic and the impact of uncertainties, mitigation strategies, and underreporting of cases in South Korea, Italy and Brazil. *Chaos Solitons Fractals*, **136** (2020), 109888. https://doi.org/10.1016/j.chaos.2020.109888

20. *NHS England*, NHS Payment System, Available from: https://www.england.nhs.uk/pay-syst/.

21. *Department of Health*, Reference costs 2015-2016, Available from: https://www.gov.uk/government/publications/nhs-reference-costs-2015-to-2016.

22. H. Thom, J. Walker, P. Vickerman, W. Hollingworth, Exploratory comparison of healthcare costs and benefits of the UK's Covid-19 response with four European countries, *Eur. J. Public Health*, **31** (2021), 619-624. https://doi.org/10.1093/eurpub/ckab019

23. M. Beaussier, E. Vanoli, F. Zadegan, H. Peray, E. Bezian, J. Jilesen, et al., Aerodynamic analysis of hospital ventilation according to seasonal variations. A simulation approach to prevent airborne viral transmission pathway during Covid-19 pandemic, *Environ. Inte.*, **158** (2022), 106872. https://doi.org/10.1016/j.envint.2021.106872

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