Journal of Hospital Infection 152 (2024) 81–92

Available online at www.sciencedirect.com

Journal of Hospital Infection

journal homepage: www.elsevier.com/locate/jhin

Admission screening testing of patients and staff N95 respirators are cost-effective in reducing COVID-19 hospital-acquired infections

F. McAndrew [a,*], R.G. Abeysuriya [a,b], R. Sacks-Davis [a,b], M. Sammann [c], D.M. Lister [c], D. West [c], S.S. Majumdar [a,b], N. Scott [a,b]

[a] Burnet Institute, Melbourne, Victoria, Australia
[b] Department of Epidemiology and Preventive Medicine, Monash University, Melbourne, Victoria, Australia
[c] Victorian Government Department of Health, Victoria, Australia

ARTICLE INFO

Article history:
Received 16 April 2024
Accepted 10 June 2024
Available online 15 July 2024

Keywords:
COVID-19
Agent-based model
Outbreak
Acute care
Hospital-acquired infections
Cost-effectiveness

SUMMARY

Background: Coronavirus disease 2019 (COVID-19) outbreaks in acute care settings can have severe consequences for patients due to their underlying vulnerabilities, and can be costly due to additional patient bed-days and the need to replace isolating staff. This study assessed the cost-effectiveness of clinical staff N95 respirators and admission screening testing of patients to reduce COVID-19 hospital-acquired infections.

Methods: An agent-based model was calibrated to data on 178 outbreaks in acute care settings in Victoria, Australia between October 2021 and July 2023. Outbreaks were simulated under different combinations of staff masking (surgical, N95) and patient admission screening testing [none, rapid antigen test (RAT), polymerase chain reaction]. For each scenario, average diagnoses, COVID-19 deaths, quality-adjusted life years from discharged patients, and costs (masks, testing, patient COVID-19 bed-days, staff replacement costs while isolating) from acute COVID-19 were estimated over a 12-month period.

Findings: Compared with no admission screening testing and staff surgical masks, all scenarios were cost saving with health gains. Staff N95 respirators + RAT admission screening of patients was the cheapest scenario, saving A$78.4M [95% uncertainty interval (UI) 44.4M–135.3M] and preventing 1543 (95% UI 1070–2146) deaths state-wide per annum. Both interventions were individually beneficial: staff N95 respirators saved A$54.7M and 854 deaths state-wide per annum, while RAT admission screening of patients saved A$57.6M and 1176 deaths state-wide per annum.

Interpretation: In acute care settings, staff N95 respirators and admission screening testing of patients can reduce hospital-acquired COVID-19 and COVID-19 deaths, and are cost saving because of reduced patient bed-days and staff replacement needs.

* Corresponding author. Address: Burnet Institute, 85 Commercial Rd, Melbourne, VIC 3004, Australia.
E-mail address: Fenella.McAndrew@burnet.edu.au (F. McAndrew).

https://doi.org/10.1016/j.jhin.2024.06.015

Introduction

The prevention and reduction of healthcare-associated infections is a major priority in Australia and globally due to the increased vulnerability of patients [1]. Hospital-acquired coronavirus disease 2019 (COVID-19) occurs when patients admitted for non-COVID-19 reasons acquire COVID-19 following exposure to staff, other patients or visitors, and infection prevention and control measures are insufficient to prevent transmission. As well as being a patient safety risk, hospital-acquired infections carry significant costs to the health system [2–4]. Hospital-acquired COVID-19 first emerged as an issue in Australia in 2020 among healthcare workers, then among patients from the end of 2021 as community transmission was widespread [5]. In the state of Victoria, 15–25% of patients in hospital with COVID-19 between June 2022 and June 2023 acquired their infection after admission, with 90-day mortality of 18.9% compared with 12.3% among matched patients who did not acquire COVID-19 post admission (see online Supplementary material). This compares with similar numbers globally, with 2021 estimates suggesting that 11.3% of hospitalized COVID-19 patients in the UK acquired COVID-19 whilst in hospital [6], 11.8% in Germany [7], and 9.2% in Brazil [8].

Within acute care facilities, patients who acquire COVID-19 following admission require isolation and transmission-based precautions to limit onward transmission, and may require longer hospital stays than if they had not acquired COVID-19 [9–11]. Healthcare workers who are diagnosed with COVID-19 require time off work to isolate and recover, which has costs associated with sick leave and replacement staff. Particularly during periods of high COVID-19 community transmission, hospital-acquired infections can compound health system performance challenges through additional hospital demand and staff absence [12,13]. In addition to these impacts from acute infection, it is well established that COVID-19 causes chronic or longer-term impacts, known as 'long COVID' or post-acute sequelae, which are more pronounced in people admitted for COVID-19 [14,15].

During the emergency phase of the pandemic (2020–2023), multi-layered infection prevention and control interventions were applied in acute care settings to protect staff and patients from contracting COVID-19, and to prevent outbreaks [16]. These measures, outside of outbreak management protocols, included routine COVID-19 screening testing of staff, visitors and patients; staff vaccine mandates; staff and visitor mask requirements; strengthened ventilation, air flow and air filtration; grouping of suspected COVID-19 cases; isolation areas and wards for confirmed cases; and limiting visitor capacity [11,17]. As Australian government emergency pandemic orders and directions ended in 2023 and jurisdictions reverted to COVID-19 infection control and prevention guidance, there was variability between the application of interventions [18]. Over 2023, many acute care settings ceased testing patients on admission, and shifted from use of N95 respirators to surgical masks by staff, while some settings have adapted more dynamic approaches of increasing/decreasing intervention layers based on community prevalence and, hence, risk of incursion [19,20].

As COVID-19 continues to cause epidemic transmission and impacts, understanding the cost-effectiveness of interventions to prevent COVID-19 transmission in acute care settings is crucial for informing ongoing changes to policy and practice. However, while other studies have used agent-based epidemiological models to simulate COVID-19 outbreaks in hospitals and acute care facilities [21–23], none, to the authors' knowledge, have used these outputs to estimate the cost-effectiveness of interventions. This study aimed to estimate the cost-effectiveness of staff N95 respirators and admission screening testing of patients in acute care settings. The model uses data on outbreaks in acute care settings from the state of Victoria, Australia, but would have implications for other settings given the widespread nature of hospital-acquired infections.

Methods

Data

Data on outbreaks occurring in Victorian acute care settings were aggregated from multiple sources, consisting of the outbreak size (number of patient and staff diagnoses), outbreak duration, and the corresponding demographic composition of each setting that recorded an outbreak (number of admissions, age distribution of admissions, distribution of length of stay, staff:patient ratio). The Victorian Nosocomial Infection Surveillance System was used to collect all data for this study [17].

The Victorian Department of Health maintained a hospital minimum dataset collated from hospitals across the state, and included data from 50 outbreaks in acute care settings from August 2021 to April 2022. Each of the outbreaks contained complete information about number of patient diagnoses, outbreak duration and demographic composition; however, approximately 75% of outbreaks recorded zero staff diagnoses. The dataset, while detailed, is thought not to contain all outbreaks in that period. Following consultation with hospital staff, the dataset was thought to be unreliable for staff outcomes as systematic staff screening was not widely implemented in 2022, and community diagnoses were not recorded by hospitals. Alternate data were sought to inform the outbreak size distribution among staff.

Additional acute care outbreak data not included in the hospital minimum dataset were obtained by the Department of Health from Hospital A (metropolitan private healthcare facility; 98 outbreaks between March 2022 and June 2023), Network A (containing a regional healthcare facility; six outbreaks between November 2022 and April 2023) and Hospital B (metropolitan tertiary healthcare facility; 24 outbreaks between November 2022 and May 2023). Only data relating to the Omicron period was considered, and all additional outbreak data included information on patient diagnoses and demographic composition of each setting. All except Hospital A included outbreak duration, and Hospital A was the only facility to include staff diagnoses.

Among all datasets, a combined total of 178 outbreaks was available from the Omicron circulation period.

Model overview

An established agent-based model, Covasim [24], was used to simulate outbreaks in acute care settings under different intervention scenarios. The model is available online [25], and has been used previously to model epidemic waves and

response strategies in Australia [26–29]. For this analysis, a detailed acute care setting component was constructed, based on previous work simulating outbreaks in schools [30] and aged care settings [31].

Acute care wards are highly heterogeneous in terms of the health facility characteristics, the patient population, the ward built environment and staff characteristics. They may include short stay units, general wards (medicine, surgery) and speciality wards (cancer, maternity, paediatric) for example, and are located in rural or metropolitan areas. For the purposes of this study, these represent locations where patients are admitted (with some underlying health conditions or vulnerability), often for overnight stays, who, throughout their stay, would have interactions with healthcare workers, receive visitors, and may be in close proximity to other patients.

Data sparsity did not allow for meaningful disaggregation of outcomes by ward type, so the unit of analysis for this study is an 'average' acute care ward in Victoria, Australia. These average wards were simulated by sampling over different acute care ward characteristics, such that outcomes relate to an average acute care ward. As a result, certain outlier ward types were excluded from analysis, specifically dialysis units (as their high number of admissions and short length of stay likely results in an overestimate of bed places within the unit) and dementia wards (as they had an average age of >80 years, and age is likely a confounder but data are not available to reflect accurately), and so the results may not apply to these settings. The wards that have been excluded can be seen in Appendix A, Figure S2 (see online supplementary material).

Each acute care setting was modelled to have patients and staff, with characteristics parametrized by settings in the hospital minimum dataset. A normal distribution was fit to patient numbers per setting to use as a model input (estimated in the data for each setting by dividing total patient admissions by median length of stay), which had a mean of 28 patients per setting and standard deviation of 14. The central 95th percentile for patient age was 45–75 years. Number of staff per setting was calculated based on staff:patient ratio, which was most commonly 1:3. In the model, staff were selected from the general population aged 18–65 years. Further details are available in Appendix A (see online supplementary material).

Outbreak simulations

Within acute care settings, three types of interactions were modelled: patient–patient, staff–staff and staff–patient (Figure 1). Visitors were not modelled explicitly, but would have been the origin of some of the incursions among patients in the model.

The model generates a single acute care setting at random (i.e. sampling patient numbers from the setting size distribution, staff numbers from the staff:patient ratio, and generating a facility with those characteristics), and then simulates a single incursion by infecting a patient or staff member at random. Data on the source of incursion were available in the Hospital A dataset and used to inform the simulations, with 74% of outbreaks having index cases reported as staff and 26% as patients (unknown or visitor were excluded).

Following an incursion, transmission can occur between contacts, and symptomatic testing (staff and patients) is required to detect the first case. Once a case is identified, the whole setting is tested once by polymerase chain reaction (PCR), and all positive cases are assumed to isolate. On

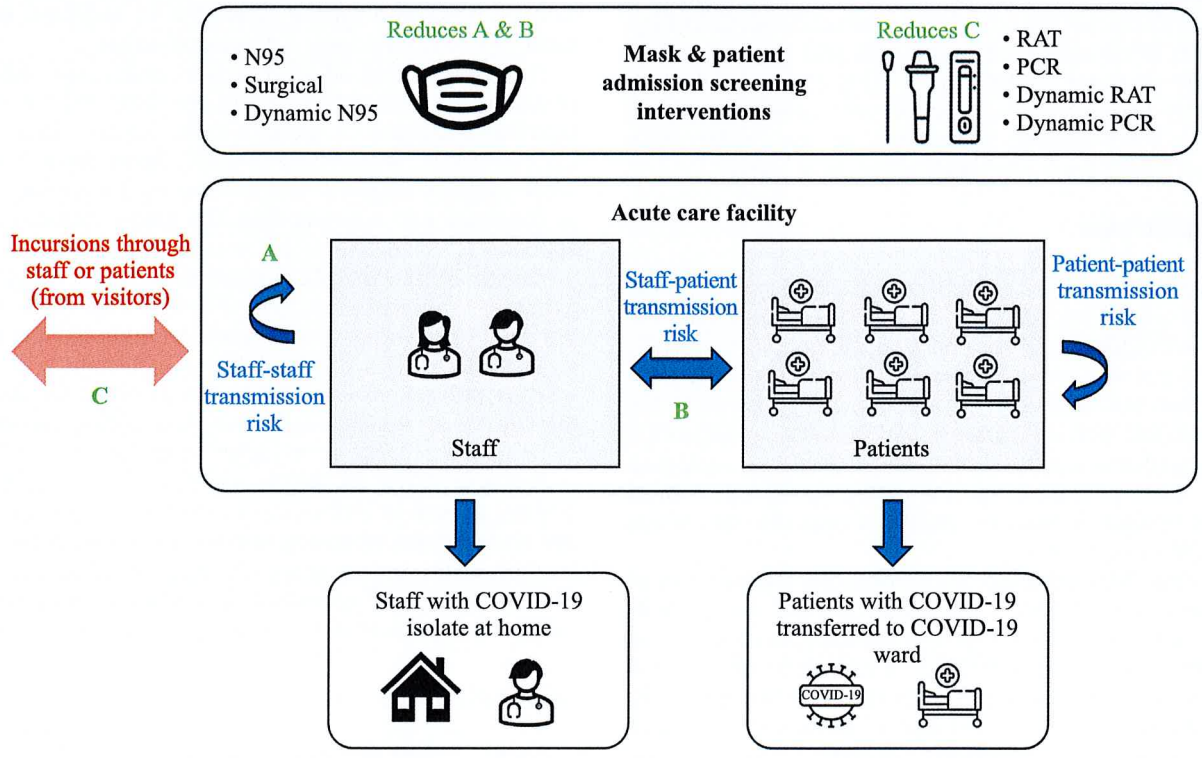

Figure 1. Model schematic displaying the incursion source and three types of mixing in acute care facilities. RAT, rapid antigen test; PCR, polymerase chain reaction; COVID-19, coronavirus disease 2019.

detection of the first case, setting-wide risk mitigations are introduced in the model that reduce the risk of transmission by 66% (calibrated to fit outbreak duration data).

Within the model, both patients and staff have a probability of testing if symptomatic of 60% per week, and staff have a probability of testing if asymptomatic of 10% per week, which were both chosen as reasonable estimates. Testing of patients is assumed to be done using PCR and testing of staff using rapid antigen tests (RATs).

At the end of each simulation, the total number of infections and diagnoses are recorded for patients and staff, as well as the duration of the outbreak. Patient COVID-19 deaths per outbreak were estimated by multiplying diagnoses by the average observed case fatality rate for hospital-acquired infections in Victoria (Appendix A, see online supplementary material).

Interventions

The model includes options for staff mask wearing (N95 or surgical) and admission screening testing of patients (PCR or RATs; with PCR being more sensitive but taking 24 h to return results). PCR testing has sensitivity of 87% [32] and RATs have sensitivity of 77.3% [32,33].

The scenario used for calibration assumes that admission screening testing of patients occurs, and staff wear N95 respirators, reflecting the typical health service policies in place in Victorian health services at the time the outbreak data were recorded. As admission and discharge of patients from an acute care facility were not modelled explicitly, admission screening testing of patients was approximated by testing agents on average twice per week, in line with an average length of stay of 4.1 days from the hospital minimum dataset.

The effectiveness of surgical masks compared with N95 respirators was taken from a cohort study by Dorr *et al.* [34] {odds ratio (OR) 0.56 [95% confidence interval (CI) 0.43–0.74]}. The impact of no masks compared with N95 respirators was taken from a study by Kim *et al.* [35] [OR 0.29 (95% CI 0.19–0.44)]. Both studies supplied ORs per interaction, and are applied to staff–patient interactions in the model, with staff–staff interactions assuming bidirectional impact.

Model calibration

The model was calibrated to fit the distribution of staff and patient infections per outbreak, as well as outbreak duration (Figure 2 and Appendix C, see online supplementary material). Staff outbreak size distribution was calibrated to Hospital A data; patient outbreak size distribution was calibrated to the pooled hospital minimum dataset, and Hospital A, Network A and Hospital B datasets (total combined dataset); and outbreak duration was calibrated to the total combined dataset excluding Hospital A data, as Hospital A data did not include total length of outbreaks.

Calibration was achieved by varying the relative risk of transmission per contact, the mean number of contacts between staff and patients, and the risk reduction on detection of the first case. The probability of an incursion occurring in staff vs patients was increased slightly to 85% so that the model could reproduce the large number of outbreaks with zero patient infections. Parameters were chosen so that, over 1000 simulations, the model aligned with the data while still being realistic (i.e. staff having more contacts than patients).

The model was calibrated assuming intervention and policy conditions [e.g. vaccine coverage and exposure immunity (Appendix A, see online supplementary material)] as per January 2022, because this represents the largest number of outbreaks in the data.

Scenarios: average acute care outcomes per 100 incursions

First, an incursion-outcome library was established to record the distribution of outcomes per 100 incursions under different interventions. All combinations of the following scenarios were run:

- mask usage: N95, surgical (baseline), 'dynamic' masks.
- admission screening testing: patients on admission with PCR, patients on admission with RATs, none (baseline), 'dynamic' testing

Dynamic strategies were defined as being in place only during periods of high community prevalence [see Appendix D (online supplementary material) for definition], which was estimated to be 63.4% of the time in Victoria between June 2022 and June 2023. These periods of high community transmission accounted for 77% of diagnoses in acute care (Appendix B, see online supplementary material). Hence the dynamic scenarios assumed the intervention costs for 63.4% of the time, but intervention benefits for 77% of simulated incursions.

Scenarios: average outcomes per scenario per acute care setting over a 12-month period

The incursion-outcome libraries were combined with other data on hospital-acquired infections to estimate expected state-wide outcomes over a 12-month period.

The total number of incursions in acute care settings per annum was estimated by taking the total patient hospital-acquired infections in Victoria from January 2022 to June 2023 (N=6023), annualizing (N=4853; Appendix B, see online supplementary material) and dividing by the average number of diagnoses per outbreak from the model calibration (N=2; Appendix C, see online supplementary material).

For scenarios with RATs or no admission screening testing of patients, additional incursions were modelled compared with the data, as fewer infections would be detected and diverted on admission. The average additional incursions in acute care settings per annum were estimated as the total detections through the screening programme (June 2022–June 2023).

For each scenario, total patient diagnoses, staff diagnoses and patient COVID-19 deaths per acute care setting per 12 months, as well as differences to the baseline (surgical masks and no admission screening testing), were calculated. Median and 95% uncertainty intervals (UI) for each scenario (defined as the 2.5th and 97.5th quantiles), and differences between scenarios, were estimated by repeating this sampling process.

Health outcomes

Gains in total quality-adjusted life years (QALYs) among acute care patients were calculated for each scenario compared with no patient admission screening and staff surgical

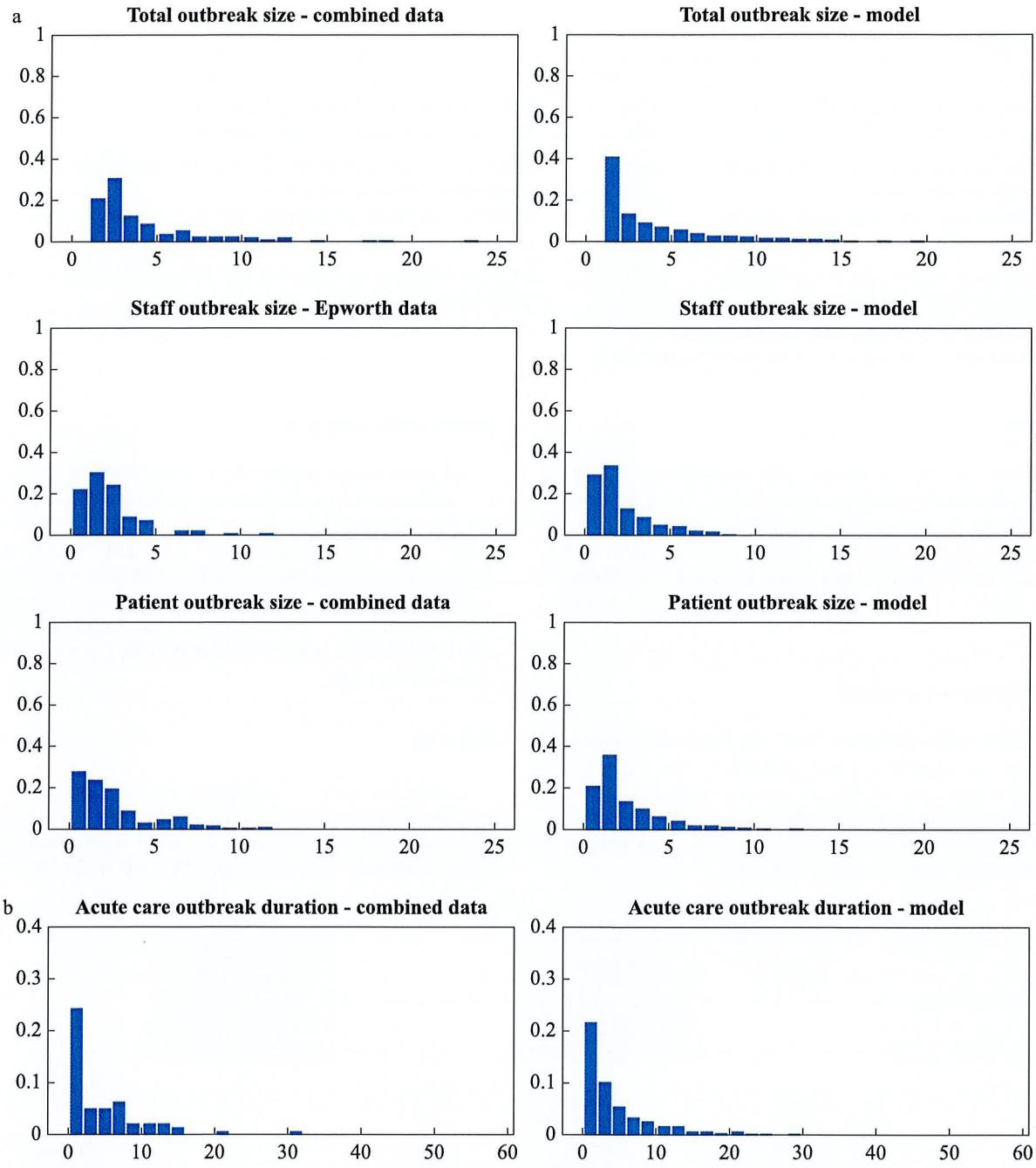

Figure 2. Model calibration. (a) Outbreak size calibration: (left) distribution of total, staff and patient outbreak sizes from Victorian acute care data; (right) distribution of model estimates of total, staff and patient outbreak sizes. (b) Outbreak duration distribution: (left) distribution of outbreak duration from Victorian acute care data; (right) distribution of model estimates of outbreak duration.

masks. QALY gains were based on state-wide reductions in COVID-19 deaths throughout the simulated 12-month intervention period. Reduced health utility during acute COVID-19 and post COVID-19 conditions, such as long COVID, were not included in this study, meaning these are highly conservative estimates for QALYs gained from interventions. A lifetime time horizon was used for QALY gains, with future gains discounted at 5% per annum. COVID-19 case fatality rates among acute care patients were estimated from hospital data during the Omicron period, which also accounted for high vaccine coverage. The QALYs gained from a COVID-19 death averted varied depending on the age of patients in the simulated acute care setting, and were based on the average remaining life expectancy for people of that age (Appendix A, see online supplementary material). This was then multiplied by a comorbidity adjustment of 55% to reflect the fact that those presenting to acute care have, on average, lower quality of life.

Table I
Model cost inputs

Cost component	Cost (A$)	Source
N95 respirators (state-wide annual cost)	18.9M	Investment and health sector budgeting
Surgical masks (state-wide annual cost)	4.9M	Investment and health sector budgeting
PCR admission screening testing of patients (state-wide annual cost)	23.6M	Victorian Admitted Episodes Dataset and commercial and HealthShare Victoria estimates
RAT admission screening testing of patients (state-wide annual cost)	1.2M	Victorian Admitted Episodes Dataset and commercial and HealthShare Victoria estimates
Patient bed costs (mean cost per infection)	1595/day	National Weighted Activity Unit and 2022/23 National Efficient Price
Staff (mean cost per infection)	308/day	Investment and health sector budgeting

PCR, polymerase chain reaction; RAT, rapid antigen test.
Methods and details of calculations can be found in Appendix B.

Cost inputs

Total costs for each scenario were calculated in 2023 A$ from the healthcare provider perspective. Costs were only considered over the 12-month intervention period, so no discounting was applied. Costs included interventions (i.e. masks, tests), additional patient bed-days required for hospital-acquired COVID-19, and staff absenteeism for isolation (Table I).

Cost-effectiveness analysis

State-wide COVID-19 deaths, total QALYs and total costs per annum were calculated for each scenario. The incremental cost-effectiveness ratio (ICER; difference in costs divided by difference in QALYs) was calculated for each scenario compared with the baseline of no admission screening testing of patients and staff surgical masks (Figure 2).

Uncertainty analysis

A multi-variate probabilistic uncertainty analysis was used to combine uncertainty from all parameters and generate 95% UIs for outcomes, as well as the probability that scenarios would be cost-effective for different willingness-to-pay thresholds. Uncertainty in COVID-19 deaths per scenario, and difference from the baseline, were estimated by sampling the incursion-outcome libraries repeatedly. Uncertainty ranges for other parameters are given in Appendix C (see online supplementary material).

Results

Compared with a reference of no admission screening testing of patients and staff surgical masks, all scenarios were cost saving with health gains over a 12-month period (Figures 3 and 4, Table II). This is because the testing or N95 costs were

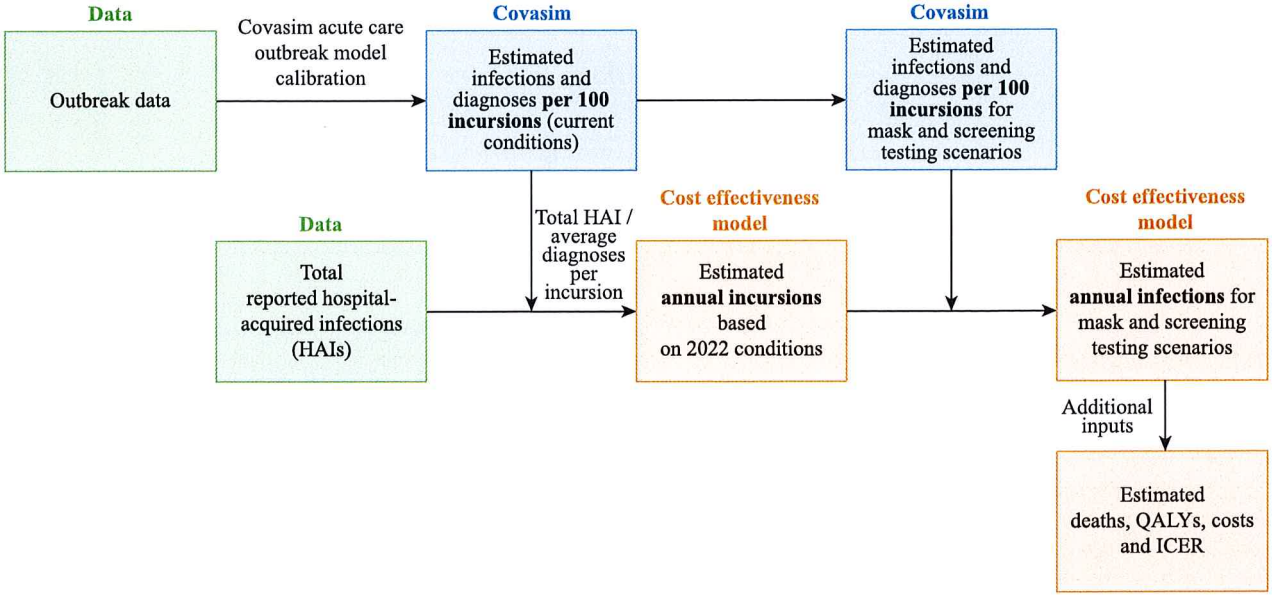

Figure 3. Model workflow. Inputs from the acute care agent-based model (blue) use outbreak data inputs (green). The agent-based model runs and hospital-acquired infection data are used to calculate cost-effectiveness of different interventions (orange). QALYs, quality-adjusted life years; ICER, incremental cost-effectiveness ratio.

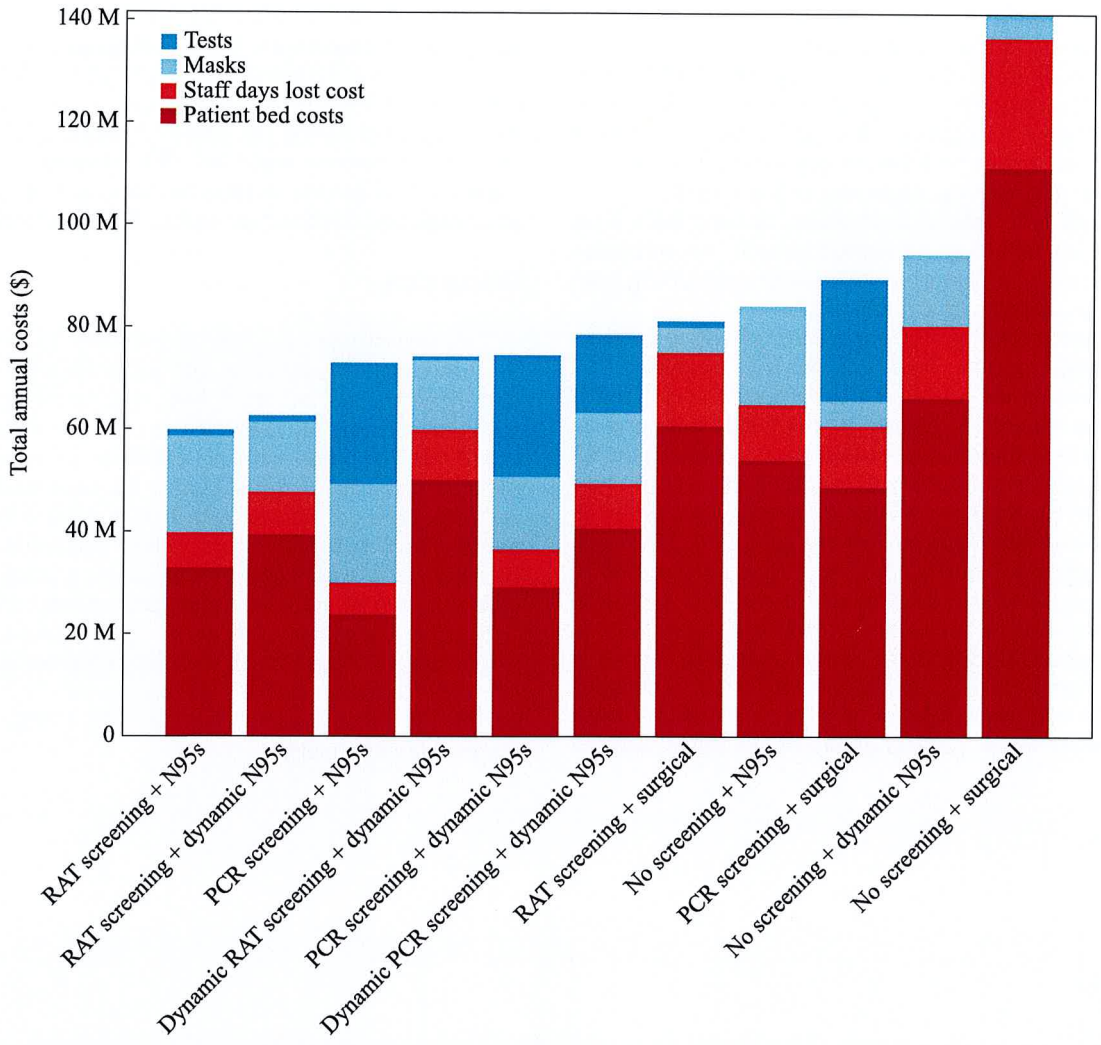

Figure 4. Total costs of different scenarios. Scenarios are ordered from lowest to highest annual costs. Patient bed costs (red) are proportional to deaths and quality-adjusted life years. RAT, rapid antigen test; PCR, polymerase chain reaction.

Table II
Difference in costs, quality-adjusted life years (QALYs) and deaths for each scenario compared with no patient admission screening testing and use of surgical masks by staff

Patient admission screening testing	Staff masks	Difference in costs (intervention + bed-days + staff absence) (A$)	Difference in QALYs	Difference in COVID-19 deaths
None	Surgical	Reference	Reference	Reference
PCR	N95	-62.6M (-133.3M to -22.1M)	10,830 (6417–15,935)	-1684 (-2478 to -998)
RAT	N95	-78.4M (-135.3M to $-44.4M)	9,922 (6883–13,795)	-1543 (-2146 to -1070)
None	N95	-54.7M (-91.9M to -30.1M)	5484 (3727–7497)	-854 (-1167 to -580)
PCR	Surgical	-49.7M (-113.3M to -7.4M)	9018 (3941–14,151)	-1402 (-2201 to -613)
RAT	Surgical	-57.6M (-102.2M to -36.0M)	7556 (5120–10,818)	-1176 (-1683 to -797)
PCR	Dynamic	-61.3M (-131.2M to -21.6M)	10,456 (5827–15,458)	-1,626 (-2404 to -906)
RAT	Dynamic	-76.3M (-129.0M to -45.2M)	9361 (6479–13,048)	-1456 (2030 to -1007)
None	Dynamic	-45.3M (-74.2M to -26.2M)	4146 (2825–5699)	-645 (-887 to -439)
Dynamic RAT	Dynamic	-64.8M (-109.3M to -38.0M)	8074 (5604–11,224)	-1256 (-1746 to -871)
Dynamic PCR	Dynamic	-58.6M (-113.6M to -28.0M)	9126 (6345–12,862)	-1419 (-2000 to -987)

PCR, polymerase chain reaction; RAT, rapid antigen test; COVID-19, coronavirus disease 2019.

small in comparison with the cost of additional patient bed-days due to hospital-acquired infections.

Staff N95 respirators were cost saving with health gains compared with surgical masks regardless of admission screening testing strategy for patients. RAT admission screening of patients was cost saving with health gains compared with no admission screening testing, regardless of staff masks.

With dynamic N95 respirators in place, dynamic RATs were cost saving with health gains compared with no admission screening testing, and full-time RATs were cost saving with health gains compared with dynamic RATs.

RAT admission screening of patients and staff N95 respirators was the cheapest option. From this scenario, adopting PCR admission screening was necessary to increase impact, but it was also more expensive (Figure 3). Outcomes following an outbreak were similar (with the increased test sensitivity of PCR negated by slower results), but PCR testing prevented more incursions through detection of more asymptomatic cases on admission. Moving from RATs to PCR had an ICER of $7449 and $45 per QALY gained if staff were using N95 or surgical masks, respectively, or $3710 per QALY gained if dynamic admission screening of patients and dynamic staff N95 respirators were in place. In the uncertainty analysis, there was a 90% chance of PCR being cost-effective compared with RAT admission screening at a willingness-to-pay of $43k and $27k per QALY gained with staff N95 or surgical masks, respectively, and $9k per QALY gained if dynamic admission screening and dynamic staff N95 respirators were in place (Figures 5, 6, Table III).

PCR admission screening and staff N95 respirators shows the most QALYs gained, with PCR admission screening and dynamic N95 respirators having the second highest QALYs gained. RAT admission screening and staff N95 respirators has the third highest QALYs gained of the scenarios, but has the best cost advantage due to the lower cost of RATs compared with PCR.

Discussion

This analysis used an agent-based model to simulate COVID-19 outbreaks in acute care settings in Victoria to assess the cost-effectiveness of staff N95 respirators and admission screening testing of patients to reduce hospital-acquired COVID-19. Compared with no admission screening testing of patients and staff surgical masks, all combinations of interventions were cost saving with health gains over a 12-month period. Staff N95 respirators + RAT admission screening of patients was the cheapest option, saving an estimated $78.4M (95% UI 44.4M–135.3M) and preventing 1543 (95% UI 1070–2146) deaths state-wide per annum. Staff N95 respirators + PCR admission screening of patients was the most effective option, saving an estimated $62.6M (95% UI 22.1M–133.3M) and preventing 1684 (95% UI 998–2478] deaths state-wide per annum.

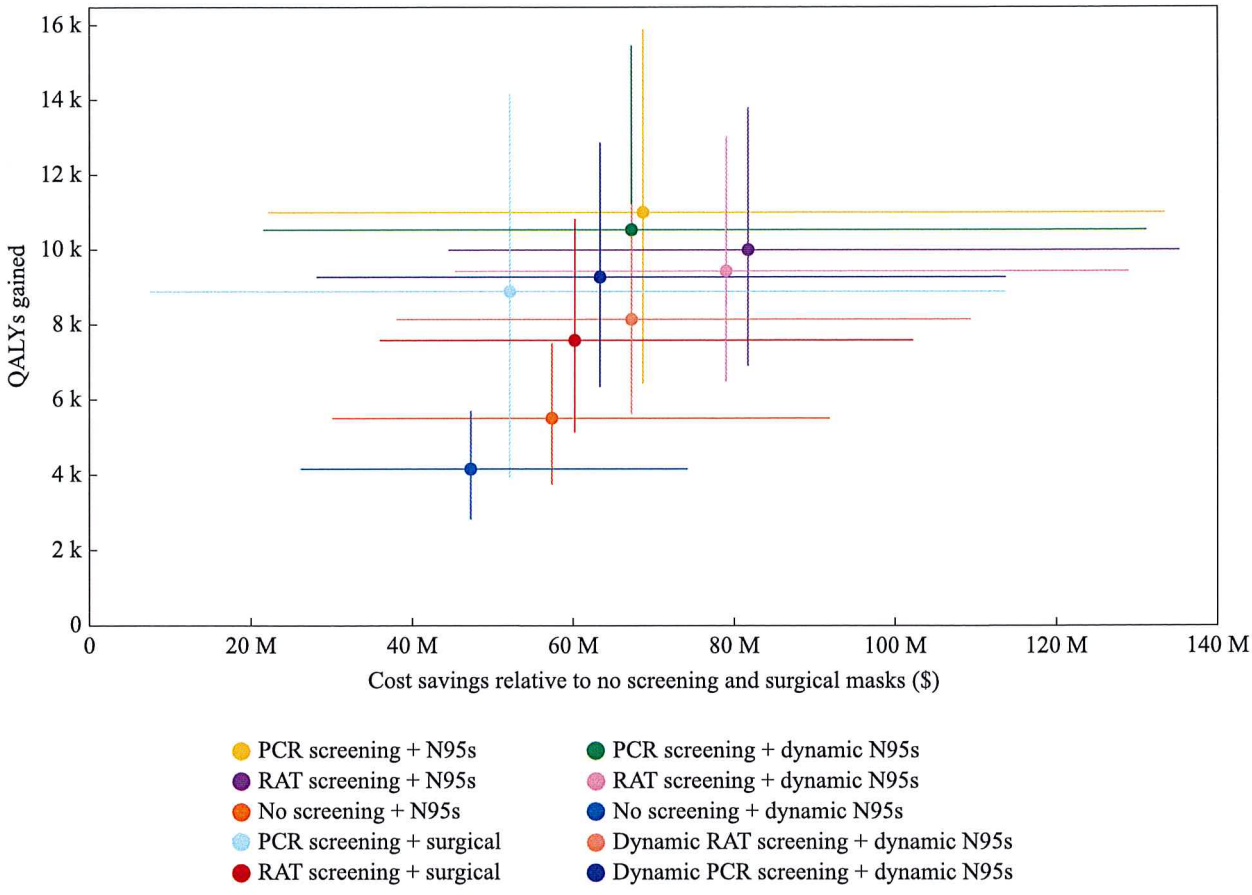

Figure 5. Cost-effectiveness plane. All scenarios were cost saving compared with no patient admission screening testing and use of surgical masks by staff. RAT, rapid antigen test; PCR, polymerase chain reaction; QALYs, quality-adjusted life years.

Table III
Difference in costs, quality-adjusted life years (QALYs) and deaths for different mask types when moving from rapid antigen test (RAT) to polymerase chain reaction (PCR) admission screening testing

Admission screening testing	Staff masks	Difference in costs (A$)	Difference in QALYs	Difference in deaths	ICER (A$ per QALY gained)	90% percentile of ICER
Cost-effectiveness of moving from RAT to PCR admission screening, with use of N95 respirators by staff						
PCR	N95	13.6M (−6.2M to 32.0M)	1056 (−664 to 2581)	−164 (−401 to 104)	7449 (−144,385 to 341,169)	$43k per QALY gained
RAT	N95	Reference	Reference	Reference	Reference	Reference
Cost-effectiveness of moving from RAT to PCR admission screening, without use of N95 respirators by staff						
PCR	Surgical	6.8M (−24.6M to 47.8M)	1455 (−1831 to 1689)	−226 (−656 to 285)	45 (−58,043 to 52,940)	$27k per QALY gained
RAT	Surgical	Reference	Reference	Reference	Reference	Reference
Cost-effectiveness of moving from dynamic RAT to dynamic PCR admission screening, with dynamic use of N95 respirators by staff						
Dynamic PCR	Dynamic N95	4.6M (−4.2M to 10.7M)	1120 (675–1735)	−174 (−270 to −104)	3710 (−2985 to 10,911)	$9k per QALY gained
Dynamic RAT	Dynamic N95	Reference	Reference	Reference	Reference	Reference

Incremental cost-effectiveness ratio (ICER) and 90% percentile of ICER recorded for each scenario.

This study found that either RAT or PCR screening of patients admitted to acute care settings prevents deaths and reduces costs. Compared with no admission screening testing, RAT admission screening of patients was estimated to save A$57.6M–78.4M and 1176–1543 deaths state-wide per annum, and PCR admission screening of patients was estimated to save $49.7M–53.6M and 1402–1684 deaths state-wide per annum, depending on staff masking strategy. If RAT admission screening of patients was already in place, the decision to adopt PCR testing would increase costs slightly, but could prevent more deaths and would have a 90% chance of being cost-effective at a willingness-to-pay of $43k or $27k per QALY gained if staff were wearing N95 respirators or surgical masks, respectively. It should be noted that, in some circumstances, such as rural or remote settings, if the availability of in-house PCR testing is low, increased PCR turnaround times may decrease effectiveness compared with point-of-care testing with RATs.

Masks were adopted at the start of the pandemic, with the World Health Organization recommending their use in healthcare settings in January 2020 [36], and given the predominant airborne route of transmission, N95 respirators demonstrated greater effectiveness [37,38]. This study found that staff N95 respirators in acute care settings could save $54.7M–78.4M and 854–1543 deaths state-wide per annum, depending on admission screening testing strategy. These results support recommendations for maintaining N95 respirator use among staff within acute care facilities. The effect size of N95 respirators chosen for the model represents the most conservative reasonable estimate in the literature, and a greater actual effect would result in greater cost-effectiveness of this intervention [39,40].

One of the reasons why staff N95 respirators and patient admission screening testing have been removed from many hospital protocols is the high upfront costs following the removal of emergency pandemic funding. Second, as community pandemic interventions in Victoria were reduced in late 2022, hospitals also reduced their pandemic interventions. Finally, there have been concerns regarding the environmental impact of large volumes of single- or limited-use personal protective equipment, such as masks. This creates an excess of waste for facilities to handle, which calls for the need for better sustainable waste management plans [41]. To consider some of these issues, as well as the fact that mask wearing may be a burden to staff on a full-time basis, this study also simulated a dynamic approach to interventions, where they were implemented only in times of higher community prevalence when incursions are more likely. While this strategy was not quite as effective as having the interventions in place continually, it was still greatly beneficial and cost saving, and could potentially increase the utilization of interventions in practice. Ultimately, the model scenarios suggest that the more these interventions can be utilized practically, the more lives and costs can be saved.

With substantially diminished community case ascertainment, hospital admission screening is a cornerstone of identifying periods of higher prevalence of COVID-19. Whilst Victoria also undertakes wastewater COVID-19 surveillance, a reduction in hospital admission screening testing that may occur in a dynamic testing scenario may also delay the identification of periods of higher prevalence, limiting the effectiveness of dynamic policy interventions.

This study builds on the literature around cost-effective interventions in acute care facilities. Other modelling studies have looked into the cost-effectiveness of increasing bed capacity [42,43], mechanical ventilation [44] and treatments [45,46] in acute care settings. Previous analyses have investigated the cost-effectiveness of masks and testing at whole-population level [47,48]; however, it remains a gap in the acute care literature. The present findings show that targeted testing strategies and continued mask wearing can have notable cost benefits within acute care settings. It follows that other infection prevention and control interventions with similar effectiveness, such as ventilation or newer biomedical tools, could have similar benefit. Future research on the cost-

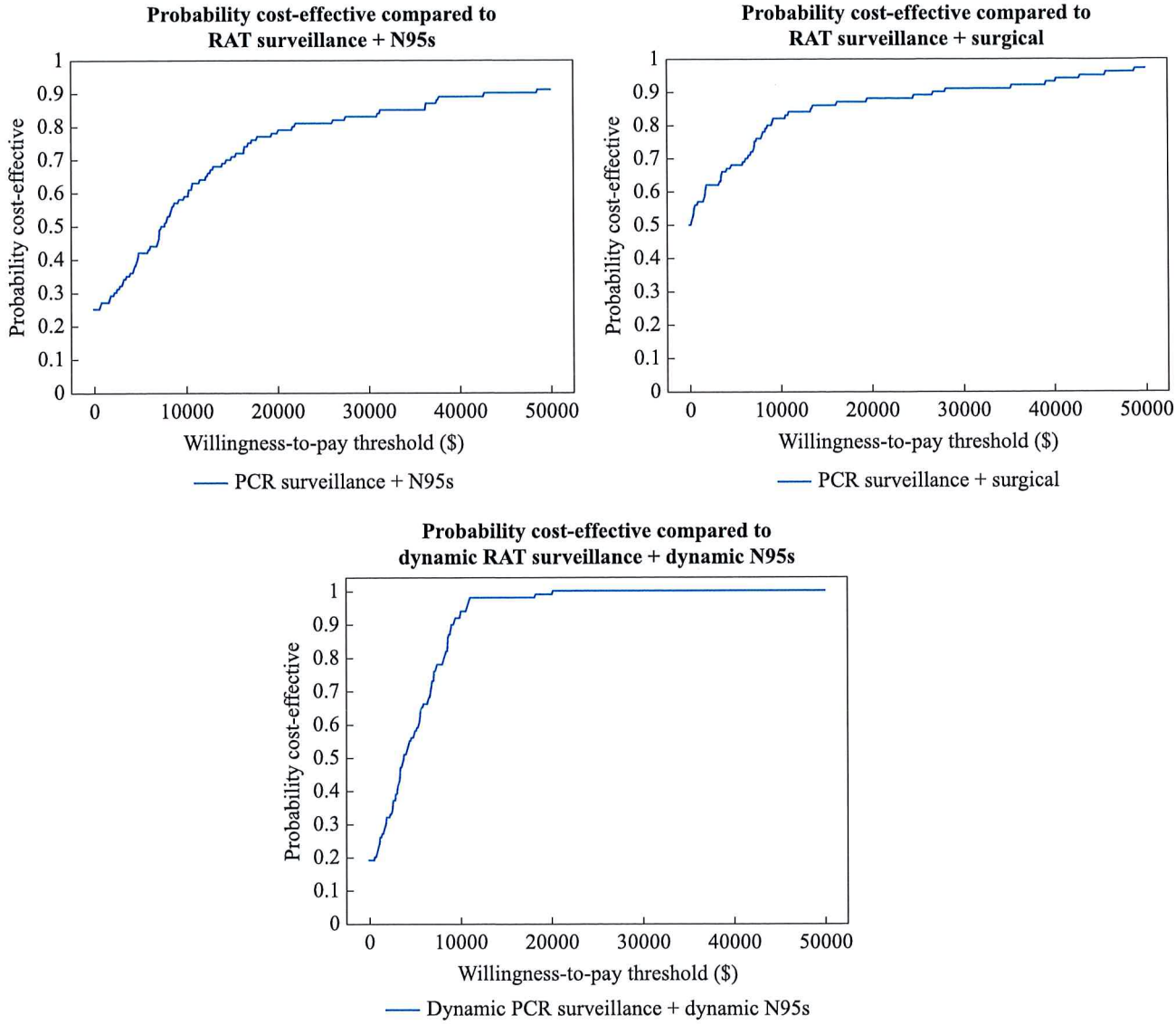

Figure 6. Probability that the scenario is cost-effective when moving from rapid antigen test (RAT) to polymerase chain reaction (PCR) admission screening testing for different mask types.

effectiveness of potentially sustainable strategies not requiring behavioural modification, such as hospital infrastructure and ventilation, is needed.

This work has some important limitations. The model simulates outbreaks while sampling over all sizes of acute care settings; however, these are highly heterogeneous settings, and outcomes should be interpreted as average state-wide values for Victoria rather than being specific to any individual setting. In particular, some settings may have higher risks of infection, depending on patient age and types of comorbidities, and this could influence costs and outbreak sizes. The outbreak model is calibrated to patient and staff diagnosis data, which has limitations as the number of hospital-acquired infections may be a large under-representation due to incomplete definitions, improper application of tests, sensitivity of tests and incomplete reporting. Future incursions into acute care settings are likely to depend on community epidemic waves, which are largely unknown; as such, the results are based on a similar number per annum as was observed in 2022. There is great uncertainty in the proportion of incursions that come from patients (or visitors) compared with staff, and a higher proportion of patient/visitor incursions compared with the 15% used for this analysis (derived from Hospital A data + calibration) would make patient admission screening testing more cost-effective. Vaccine coverage over time within acute care facilities has been approximated from whole-population vaccine coverage (Appendix A); however, coverage may be higher due to patients being considered high risk. Changes in vaccine coverage over time (including waning immunity) is likely to influence outcomes, with waning immunity increasing outbreak size and the relative impact and cost-effectiveness of interventions, and additional vaccine boosters reducing intervention impacts. Antiviral drugs and treatments for COVID-19 reduce the risk of hospitalization and death, and may reduce the risk of transmission. They were not assessed directly in the model, and data on their use for hospital-acquired infections

were not available [49]. Patients who acquired COVID-19 and required an extended length of stay in acute care may experience decreased quality of life; this was not considered in this study, meaning that this study may have underestimated the benefits of preventing infections. Reducing COVID-19 in patients and staff has the potential additional benefit of reducing the risk of long COVID. The potential impacts from masks on other airborne pathogens in acute care settings, such as influenza and respiratory syncytial virus, was not assessed within this study. Increased mask usage could have merit for multiple pathogens, and should be investigated further [50].

In conclusion, in acute care settings, staff N95 respirators and admission screening testing of patients can save lives and reduce costs related to COVID-19 through reduced patient bed-days and staff replacement needs. The more they can be implemented practically, the greater the impact is likely to be. Infection prevention and control measures to reduce COVID-19 transmission in acute care settings should continue to be applied.

Acknowledgements

SM and NS are the recipients of National Health and Medical Research Council fellowships. The authors gratefully acknowledge the support provided by the Victorian Government Operational Infrastructure Support Programme.

Conflict of interest statement
None declared.

Funding
This study was funded by the Victorian Government Department of Health, who contributed to study design, data analysis and results interpretation.

Author contributions
FM, DML, DW, SM and NS conceived the study. FM, RGA, RSD and NS developed the model. FM implemented model scenarios and analysed model outputs. MS, DML, DW and SM extracted, analysed and validated data inputs. FM, RGA and NS drafted the manuscript. All authors contributed to the final version of the manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhin.2024.06.015.

References

[1] Mitchell BG, Shaban RZ, MacBeth D, Wood CJ, Russo PL. The burden of healthcare-associated infection in Australian hospitals: a systematic review of the literature. Infect Dis Health 2017;22:117–28.
[2] Lobdell KW, Stamou S, Sanchez JA. Hospital-acquired infections. Surg Clin North Am 2012;92:65–77.
[3] Donowitz LG, Wenzel RP, Hoyt JW. High risk of hospital-acquired infection in the ICU patient. Crit Care Med 1982;10:355–7.
[4] McFee RB. Nosocomial or hospital-acquired infections: an overview. Dis Mon 2009;55:422–38.
[5] Muhi S, Irving LB, Buising KL. COVID-19 in Australian health care workers: early experience of the Royal Melbourne Hospital emphasises the importance of community acquisition. Med J Aust 2020;213:44.e1.
[6] Read JM, Green CA, Harrison EM, Docherty AB, Funk S, Harrison J, et al. Hospital-acquired SARS-CoV-2 infection in the UK's first COVID-19 pandemic wave. Lancet 2021;398:1037–8.
[7] Tauffer J, Konstantyner T, de Almeida MCS, Medeiros EA. Hospital-acquired SARS-CoV-2 infection among patients admitted to a university hospital. Braz J Infect Dis 2021;25:101637.
[8] Bonsignore M, Hohenstein S, Kodde C, Leiner J, Schwegmann K, Bollmann A, et al. Burden of hospital-acquired SARS-CoV-2 infections in Germany: occurrence and outcomes of different variants. J Hosp Infect 2022;129:82–8.
[9] Evans ME, Simbartl LA, Kralovic SM, Clifton M, DeRoos K, McCauley BP, et al. Healthcare-associated infections in Veterans Affairs acute-care and long-term healthcare facilities during the coronavirus disease 2019 (COVID-19) pandemic. Infect Control Hosp Epidemiol 2023;44:420–6.
[10] Stimson J, Pouwels KB, Hope R, Cooper BS, Presanis AM, Robotham JV. Estimation of the impact of hospital-onset SARS-CoV-2 infections on length of stay in English hospitals using causal inference. BMC Infect Dis 2022;22:922.
[11] Department of Health and Aged Care. Infection Prevention and Control Expert Group – the hierarchy of controls for minimising the risk of COVID-19 transmission. Canberra: Department of Health and Aged Care; 2022.
[12] Baker MA, Sands KE, Huang SS, Kleinman K, Septimus EJ, Varma N, et al. The impact of coronavirus disease 2019 (COVID-19) on healthcare-associated infections. Clin Infect Dis 2022;74:1748–54.
[13] Lastinger LM, Alvarez CR, Kofman A, Konnor RY, Kuhar DT, Nkwata A, et al. Continued increases in the incidence of healthcare-associated infection (HAI) during the second year of the coronavirus disease 2019 (COVID-19) pandemic. Infect Control Hosp Epidemiol 2023;44:997–1001.
[14] Xie Y, Choi T, Al-Aly Z. Long-term outcomes following hospital admission for COVID-19 versus seasonal influenza: a cohort study. Lancet Infect Dis 2024;24:239–55.
[15] Davis HE, McCorkell L, Vogel JM, Topol EJ. Long COVID: major findings, mechanisms and recommendations. Nat Rev Microbiol 2023;21:133–46.
[16] Buising KL, Williamson D, Cowie BC, MacLachlan J, Orr E, MacIsaac C, et al. A hospital-wide response to multiple outbreaks of COVID-19 in health care workers: lessons learned from the field. Med J Aust 2021;214:101.
[17] Victoria Department of Health. Personal Communication with Department of Health. Burnet Institute; 2022.
[18] Australian Government. End of COVID-19 emergency response. Canberra: Department of Health and Aged Care; 2023.
[19] Government of Western Australia. Coronavirus disease 2019 (COVID-19) infection prevention and control in Western Australian healthcare facilities. Canberra: Department of Health; 2023.
[20] Victoria Department of Health. Managing staff, visitors and outbreaks. Melbourne: Victoria Department of Health; 2023.
[21] Martos DM, Parcell BJ, Eftimie R. Modelling the transmission of infectious diseases inside hospital bays: implications for COVID-19. Math Biosci Eng 2020;17:8084–104.
[22] Overton CE, Pellis L, Stage HB, Scarabel F, Burton J, Fraser C, et al. EpiBeds: data informed modelling of the COVID-19 hospital burden in England. PLoS Comput Biol 2022;18:e1010406.
[23] Park Y, Sylla I, Das AK, Codella J. Agent-based modeling to evaluate nosocomial COVID-19 infections and related policies. Nature 2021;3.
[24] Kerr CC, Stuart RM, Mistry D, Abeysuriya RG, Rosenfeld K, Hart GR, et al. Covasim: an agent-based model of COVID-19 dynamics and interventions. PLoS Comput Biol 2021;17:e1009149.
[25] Institute for Disease Modeling. Covasim mode. Seattle, WA: Institute for Disease Modelling; 2021. Available at: https://github.com/InstituteforDiseaseModeling/covasim.

[26] Scott N, Palmer A, Delport D, Abeysuriya R, Stuart RM, Kerr CC, et al. Modelling the impact of relaxing COVID-19 control measures during a period of low viral transmission. Med J Aust 2021;214:79—83.
[27] Abeysuriya RG, Delport D, Stuart RM, Sacks-Davis R, Kerr CC, Mistry D, et al. Preventing a cluster from becoming a new wave in settings with zero community COVID-19 cases. BMC Infect Dis 2022;22:232.
[28] Scott N, Abeysuriya RG, Delport D, Sacks-Davis R, Nolan J, West D, et al. COVID-19 epidemic modelling for policy decision support in Victoria, Australia 2020—2021. BMC Public Health 2023;23:988.
[29] Delport D, Sacks-Davis R, Abeysuriya RG, Hellard M, Scott N. Lives saved by public health restrictions over the Victorian COVID-19 Delta variant epidemic wave, Aug—Nov 2021. Epidemics 2023;44:100702.
[30] Abeysuriya RG, Sacks-Davis R, Heath K, Delport D, Russell FM, Danchin M, et al. Keeping kids in school: modelling school-based testing and quarantine strategies during the COVID-19 pandemic in Australia. Front Public Health 2023;11:1150810.
[31] McAndrew F, Sacks-Davis R, Abeysuriya R, Delport D, West D, Parta I, et al. COVID-19 outbreaks in residential aged care facilities: an agent-based modelling study. Front Public Health 2024;12:1344916.
[32] Arevalo-Rodriguez I, Buitrago-Garcia D, Simancas-Racines D, Zambrano-Achig P, Del Campo R, Ciapponi A, et al. False-negative results of initial RT-PCR assays for COVID-19: a systematic review. PLoS One 2020;15:e0242958.
[33] Muhi S, Tayler N, Hoang T, Ballard SA, Graham M, Rojek A, et al. Multi-site assessment of rapid, point-of-care antigen testing for the diagnosis of SARS-CoV-2 infection in a low-prevalence setting: a validation and implementation study. Lancet Reg Health West Pac 2021;9:100115.
[34] Dorr T, Haller S, Muller MF, Friedl A, Vuichard D, Kahlert CR, et al. Risk of SARS-CoV-2 acquisition in health care workers according to cumulative patient exposure and preferred mask type. JAMA Netw Open 2022;5:e2226816.
[35] Kim MS, Seong D, Li H, Chung SK, Park Y, Lee M, et al. Comparative effectiveness of N95, surgical or medical, and non-medical facemasks in protection against respiratory virus infection: a systematic review and network meta-analysis. Rev Med Virol 2022;32:e2336.
[36] World Health Organization. Advice on the use of masks in the community, during home care and in health care settings in the context of the novel coronavirus (2019-nCoV) outbreak: interim guidance, 29 January 2020. Geneva: WHO; 2020.
[37] Howard J, Huang A, Li Z, Tufekci Z, Zdimal V, van der Westhuizen HM, et al. An evidence review of face masks against COVID-19. Proc Natl Acad Sci USA 2021;118:e2014564118.
[38] Landry SA, Subedi D, Barr JJ, MacDonald MI, Dix S, Kutey DM, et al. Fit-tested N95 masks combined with portable high-efficiency particulate air filtration can protect against high aerosolized viral loads over prolonged periods at close range. J Infect Dis 2022;226:199—207.
[39] Chu DK, Akl EA, Duda S, Solo K, Yaacoub S, Schunemann HJ, et al. Physical distancing, face masks, and eye protection to prevent person-to-person transmission of SARS-CoV-2 and COVID-19: a systematic review and meta-analysis. Lancet 2020;395:1973—87.
[40] Wu G, Ji Q, Shi Y. A systematic review and meta-analysis of the efficacy of N95 respirators and surgical masks for protection against COVID-19. Prev Med Rep 2023;36:102414.
[41] Bhattacharjee S, Bahl P, Chughtai AA, Heslop D, MacIntyre CRJNS. Face masks and respirators: towards sustainable materials and technologies to overcome the shortcomings and challenges. Nano Select 2022;3:1355—81.
[42] Cleary SM, Wilkinson T, Tamandjou Tchuem CR, Docrat S, Solanki GC. Cost-effectiveness of intensive care for hospitalized COVID-19 patients: experience from South Africa. BMC Health Serv Res 2021;21:82.
[43] Gandjour A. How many intensive care beds are justifiable for hospital pandemic preparedness? A cost-effectiveness analysis for COVID-19 in Germany. Appl Health Econ Health Policy 2021;19:181—90.
[44] Zwerwer LR, Kloka J, van der Pol S, Postma MJ, Zacharowski K, van Asselt AD, et al. Mechanical ventilation as a major driver of COVID-19 hospitalization costs: a costing study in a German setting. Health Econ Rev 2024;14:1—17.
[45] Goswami H, Alsumali A, Jiang Y, Schindler M, Duke ER, Cohen J, et al. Cost-effectiveness analysis of molnupiravir versus best supportive care for the treatment of outpatient COVID-19 in adults in the US. Pharmacoeconomics 2022;40:699—714.
[46] Whittington MD, Pearson SD, Rind DM, Campbell JD. The cost-effectiveness of remdesivir for hospitalized patients with COVID-19. Value Health 2022;25:744—50.
[47] Neilan AM, Losina E, Bangs AC, Flanagan C, Panella C, Eskibozkurt GE, et al. Clinical impact, costs, and cost-effectiveness of expanded severe acute respiratory syndrome coronavirus 2 testing in Massachusetts. Clin Infect Dis 2021;73:e2908—17.
[48] Szanyi J, Wilson T, Howe S, Zeng J, Andrabi H, Rossiter S, et al. Epidemiologic and economic modelling of optimal COVID-19 policy: public health and social measures, masks and vaccines in Victoria, Australia. Lancet Reg Health West Pac 2023;32:100675.
[49] Van Heer C, Majumdar SS, Parta I, Martinie M, Dawson R, West D, et al. Effectiveness of community-based oral antiviral treatments against severe COVID-19 outcomes in people 70 years and over in Victoria, Australia, 2022: an observational study. Lancet Reg Health West Pac 2023;41:100917.
[50] Chiu NC, Chi H, Tai YL, Peng CC, Tseng CY, Chen CC, et al. Impact of wearing masks, hand hygiene, and social distancing on influenza, enterovirus, and all-cause pneumonia during the coronavirus pandemic: retrospective national epidemiological surveillance study. J Med Internet Res 2020;22:e21257.