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# COVID-19 passenger screening to reduce travel risk and translocation of disease

Lindsay L. Waite, Ahmad Nahhas, Jan Irvahn, Grace Garden, Caroline M. Kerfonta, Elizabeth Killelea, William Ferng, Joshua J. Cummins, Rebecca Mereness, Thomas Austin, Stephen Jones, Nels Olson, Mark Wilson, Benson Isaac, Craig A. Pepper, Iain S. Koolhof and Jason Armstrong

The Boeing Company, Arlington, Virginia, United States

## Original Paper

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**Corresponding author:**
Iain S. Koolhof;
Email: iain.s.koolhof@boeing.com

## Abstract

Aviation passenger screening has been used worldwide to mitigate the translocation risk of SARS-CoV-2. We present a model that evaluates factors in screening strategies used in air travel and assess their relative sensitivity and importance in identifying infectious passengers. We use adapted Monte Carlo simulations to produce hypothetical disease timelines for the Omicron variant of SARS-CoV-2 for travelling passengers. Screening strategy factors assessed include having one or two RT-PCR and/or antigen tests prior to departure and/or post-arrival, and quarantine length and compliance upon arrival. One or more post-arrival tests and high quarantine compliance were the most important factors in reducing pathogen translocation. Screening that combines quarantine and post-arrival testing can shorten the length of quarantine for travelers, and variability and mean testing sensitivity in post-arrival RT-PCR and antigen tests decrease and increase with the greater time between the first and second post-arrival test, respectively. This study provides insight into the role various screening strategy factors have in preventing the translocation of infectious diseases and a flexible framework adaptable to other existing or emerging diseases. Such findings may help in public health policy and decision-making in present and future evidence-based practices for passenger screening and pandemic preparedness.

## Introduction

The rapid global spread of the coronavirus disease 2019 (COVID-19), caused by the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) virus, has led to significant impacts to public health and economies worldwide. In response to the emergence of COVID-19, countries have imposed pandemic-related restrictions to prevent and limit its transmission with mitigation activities including the restriction of domestic and international air travel. Since the start of the COVID-19 pandemic, the aviation industry has been one of the largest industries impacted economically, with an approximate 60% decline in global passenger travel between 2019 to 2020 and an estimated loss of $324 billion USD in gross revenue to airlines globally [1]. In reopening air travel, control measures such as passenger screening and entry requirements (e.g., vaccination and diagnostic testing), non-pharmaceutical interventions, sanitation, air improvement in airports, and current benefits of environmental control systems on aircraft have been used to minimize the translocation of COVID-19 and renew passenger confidence in air travel [2, 3]. In the beginning of the pandemic, an estimated 10% of the cases of COVID-19 were attributed to importation by international travel [4]. International travel has aided in spreading new and emerging COVID-19 variants of concern [5]. Understanding passenger screening methods and the associated translocation risks from travel between countries is essential for public health and allows governments to make informed decisions. Lessons learned from the COVID-19 pandemic will be useful in mitigating future emerging and resurging infectious diseases. In this study, we present the efficacy of test-based and quarantine-based passenger screening, hereinafter collectively referred to as screening strategies, for air travel between countries with differing COVID-19 point-prevalence levels for not only COVID-19 but for future playbooks.

Screening for COVID-19 in the air travel system has helped mitigate the spread of the COVID-19 by lowering the likely number of infectious passengers entering the air travel system and quarantining and testing individuals infected at their destination, reducing the risk of disease translocation and transmission [6, 7]. Passenger screening, as relevant to the analysis herein, employs diagnostic testing techniques, requiring travellers to provide a negative COVID-19 real-time reverse transcription polymerase chain reaction (RT-PCR) assay or rapid antigen test prior to departing, upon arrival, or both [8, 9]. Prior to the development of COVID-19 vaccines and in some regions, even after their initial introduction, diagnostic testing was almost invariably used in conjunction with quarantine upon arrival, with

quarantine periods of up to 14 days [10, 11]. This was because screening strategies, while effective at reducing translocation risk, may still miss infected travellers in the air travel system; just how many were missed was not known and depends on a myriad of factors in the types of screening tests and their timing, differing quarantine lengths, and individual differences in the disease course [12, 13]. These measures were occasionally supplemented with temperature screening as well as pre-travel advice from health departments and airlines regarding information on symptoms of COVID-19 and the importance of testing prior to travelling, though the efficacy of these supplemental methods is uncertain [14]. Since the roll-out of COVID-19 vaccine programmes, several countries began requiring international travellers to be vaccinated against COVID-19, sometimes without exception and sometimes in lieu of testing [15]. In safely resuming domestic and international air travel to that of pre-pandemic levels, data-driven, risk-based approaches are necessary when assessing the appropriate passenger screening protocols. The importance and consequences communicable diseases have in aviation have recently been recognized in the United States, with the establishment of new legislation for a National Aviation Preparedness Plan Act of 2022 to address the future risk from infectious disease outbreaks and pandemics [16].

Here our aim is to estimate and present the sensitivity of several test-based and quarantine-based passenger screening strategies and their elements, and compare the relative importance of each strategy element in predicting sensitivity. By comparing the importance of various screening methods in a travel context, informed decisions can be made by governments to help guide policy, infectious disease risk management, and public health preparedness.

## Methods

### Data

Daily data of COVID-19 infections and country population data were collected from the COVID-19 Data Repository by the Center for Systems Science and Engineering at Johns Hopkins University [17, 18]. The total number of new daily notified infections was then aggregated by country into a seven-day moving average. Using population estimates for each respective country, we calculated a seven-day point-prevalence.

Data used for model calibration of RT-PCR testing were collected from two publicly available data sets from Iceland and Canada [19–21]. Iceland implemented a screening process where eligible incoming passengers were tested using RT-PCR on arrival and 5 days post-arrival with quarantine in between. Canada implemented a screening process as part of a border study where eligible arriving international passengers were tested using RT-PCR on arrival, 7 days post-arrival, and 14 days post-arrival, with quarantine during the 14-day period.

Data used for model calibration of rapid antigen testing were based on the Abbott Laboratories BinaxNOW antigen test and collected from three data sets published in the literature [22–24]. The results from the antigen tests were compared to those from the RT-PCR test to estimate testing sensitivity and specificity discussed below.

Vaccine efficacy were taken from the University of Washington Institute for Health Metrics and Evaluation, using the vaccine effectiveness provided by the Pfizer/BioNTech vaccine against the Omicron BA.5 variant of SARS-CoV-2 [25].

### Statistical analysis

#### Monte Carlo model

Passenger screening efficacies were obtained through a Monte Carlo simulation-based analysis. The starting point of this analysis was an approach used by Quilty et al. (2020) that was modified and adapted to investigate the efficacy of passenger screening as well as differing screening methods based on vaccination status [26]. Using the methods below, we produced an individualized disease timeline for travelling passengers.

To set up the Monte Carlo simulation, a timeline of disease had to first be established. The disease timeline was broken into several time points: disease exposure, onset of symptoms (if symptoms developed), and end of the infectious (contagious) period. Disease exposure was set to occur at time zero, and all other time points were modelled as Gamma distributions, with the disease timeline being sourced from the existing literature to represent that of the Omicron variant [27, 28]. The distribution for the time to symptom onset is displayed in the supplementary appendix (Supplementary Figure A.1). The time to onset of symptoms and time to end of the infectious period were modelled as a function of time from symptom onset, or corresponding time near the time of peak viral load for those who did not develop symptoms (Supplementary Figure A.2). Given that not all infected persons will develop symptoms, the Monte Carlo simulations assume that 32.4% of infected persons are asymptomatic [28] and that 0.45% of those symptomatic [29] develop severe symptoms leading to self-quarantine and their exclusion from the air travel system prior to travel. Moreover, for simplicity, we assume that there is no transmission during the travel journey and that travellers do not become infectious during this time so that we can assess the efficacy of screening methods for infections present prior to entry into the air travel system. We further generalize that the timeline of disease is the same across all individuals, including those who are asymptomatic. Finally, it is assumed that all passengers will self-quarantine until the final test is administered such that there are no new infections after arrival and that all passengers will be fully compliant with any length of quarantine imposed unless otherwise noted.

We simulated a total of 10,000 infected passengers over a generalized flight lasting four hours. The proportion of the number of passengers vaccinated and the vaccine efficacy was manually added into the model when determining the percent of passengers vaccinated and unvaccinated. The model here does not account for individual variation in vaccination regime or waning immunity [30]. Despite the potential for differing disease timelines between the vaccination status of individuals, the U.S. Centers for Disease Control and Prevention recommends the same quarantine and masking guidelines for individuals that test positive for COVID-19, regardless of vaccination status [31, 32]. This formula takes the results of screening the 10,000 passengers with the vaccinated passenger screening strategy and then scales them using the efficacy of the vaccine and the disease point-prevalence, shown in Equation 1.

$$V_{tp} = s_{tp} V_i \tag{1}$$

where $V_{tp}$ is the proportion of individuals vaccinated that are true-positive infections, $s_{tp}$ is the simulated proportion of true-positive individuals based upon the simulated passengers set, and $V_i$ the proportion of vaccinated infected individuals. The proportions of vaccinated and unvaccinated infected as well as vaccinated and unvaccinated uninfected passengers were

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**Table 1.** Contingency table of the presence of disease among vaccinated and unvaccinated individuals

| | Vaccinated | Not vaccinated | |
|---|---|---|---|
| Infected | $V_i$ | $U_i$ | Disease point-prevalence: $p$ |
| Not infected | $V_u$ | $U_u$ | (1 - $p$) |
| | Proportion vaccinated: $v$ | (1 - $v$) | 1 |

calculated using the inputs vaccine efficacy, disease point-prevalence, and assigned proportion of passengers vaccinated. These values were then used to calculate the number of passengers that were vaccinated and infected $(V_i)$, not vaccinated and infected $(U_i)$, vaccinated and not infected $(V_u)$, and not vaccinated and not infected $(U_u)$ as represented in Table 1 and Equations 2–4.

$$p = V_i + U_i \tag{2}$$

$$(1-p) = V_u + U_u \tag{3}$$

$$v = V_i + V_u \tag{4}$$

To solve for vaccine effectiveness, we use a transformed odds ratio, described in Equation 5.

$$V_e = 1 - \left(\frac{V_i/V_u}{U_i/U_u}\right) \tag{5}$$

Equation 6 is used to solve for $U_i$ in Table 1.

$$b = \frac{1 - V_e(v-p) \pm \sqrt{(V_e(v-p)-1)^2 - 4V_e p(1-v)}}{2V_e} \tag{6}$$

From there, we can solve for all of the other values in Table 1 and are able to obtain estimated proportions of infected individuals who are vaccinated and unvaccinated.

For each infected passenger, the flight departure time was randomly placed between the time of exposure and the end of the infectious period using a uniform distribution. Our analysis did not consider infected passengers who were no longer infectious at the time of departure. That is, only active infections in which a passenger was infectious at the time of departure or would later become infectious were included. Although some infected people may continue to test positive via RT-PCR even after they are no longer infectious [33, 34], these cases are not considered here.

The effectiveness of RT-PCR and antigen testing, measured in terms of sensitivity (true-positive rate or proportion of true infections that test positive), was modelled as a function of time from exposure [35, 36]. A monotonic Hermitean spline was fitted to each individual simulated infection timeline to capture the test sensitivity. It is assumed that testing sensitivity peaks at the day of symptom onset (or approximate corresponding time point for asymptomatic infections) and then trailed off to zero at 10 days past the end of the infectious period for RT-PCR, while sensitivity for an antigen test went to zero at the end of the infectious period. The distribution of testing sensitivity over the infectious period is discussed below [23, 24, 35].

## Calibration and assessment of screening parameters

The timeline model was fitted to real-world passenger screening data from Iceland and Canada, with the parameters for RT-PCR test performance calibrated against these data. Calibration of the parameters for rapid antigen testing was conducted on published data from the United States. The RT-PCR and antigen parameters were calibrated by estimating sensitivity from the data and minimizing the mean squared error between the data sensitivity and the model sensitivity. The calibration of the parameters relied on the sensitivity profile of six parameters, each of which have differing values for antigen and RT-PCR testing (denoted by subscripts Ag for antigen testing and PCR for RT-PCR testing): a $(a_{Ag}$ and $a_{PCR})$, the probability of a person testing positive at the time of exposure; b $(b_{Ag}$ and $b_{PCR})$, (the probability of a person testing positive three days before symptoms start; $c$ $(c_{Ag}$ and $c_{PCR})$, the probability of a person testing positive when symptoms start (representative of the maximum sensitivity); $d$ $(d_{Ag}$ and $d_{PCR})$, the probability of a person testing positive three days after symptoms start; $e_{Ag}$ (for antigen testing), the probability of a person testing positive one day before the end of the infectious period; $e_{PCR}$ (for RT-PCR testing), the probability of a person testing positive at the end of the infectious period; $f_{Ag}$ (for antigen testing), the probability of a person testing positive at the end of the infectious period; and $f_{PCR}$ (for RT-PCR testing), the probability of a person testing positive ten days after the end of the infectious period. The specificity of an antigen and RT-PCR test is determined by a time-constant parameter $g_{Ag}$ and $g_{PCR}$ with $g_{Ag} = 0.950$ and $g_{PCR} = 0.998$. Based on empirical data from the literature, three other parameters remained constant in our models. In the antigen model, $a_{Ag} = 0.05$, $e_{Ag} = 0.05$, and $f_{Ag} = 0.05$. The remaining parameters $b_{Ag}$, $c_{Ag}$, and $d_{Ag}$ were then calibrated against the data. In the RT-PCR model, $a_{PCR} = 0.002$, $c_{PCR} = 0.99$, and $f_{PCR} = 0.002$. The remaining parameters, $b_{PCR}$, $d_{PCR}$, and $e_{PCR}$ were calibrated against the data.

Screening elements were assessed using sensitivity, specificity, positive predictive value (PPV), and negative predicted value (NPV) [37]. Sensitivity was estimated using the percentage of the simulated infected passengers who tested positive using the screening test of interest. Specificity was estimated using the percentage of simulated uninfected passengers who tested negative using the screening test of interest. The sensitivity and specificity of the diagnostic testing parameters and the calibrated parameters showed a 'typical' disease timeline, with symptom onset on day 5 post-exposure and with the infectious period ending on day 13 of infection (Supplementary Figures A.3 and A.4).

Sensitivity post-quarantine was calculated using the proportion of simulated infectious travellers who were past the end of the infectious period at the end of the quarantine period. Most but not all infected travellers will no longer be infectious after 14 days [38]. The NPV was calculated as the proportion of all simulated travellers (infected and uninfected) who were not infectious at the end of the 14-day period. For a 14-day quarantine with 100% compliance, all passengers were evaluated for infectiousness at the end of the 14-day period after flight arrival. For scenarios with quarantine compliance less than 100%, a randomly selected percentage of passengers were evaluated for infectiousness at the end of the full 14-day period after departure. The remaining percentage of non-quarantine-compliant passengers were evaluated for infectiousness immediately after flight arrival or after the final test for scenarios that had quarantine period after testing post-arrival.

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Model results were then summarized in terms of post-screening point-prevalence, which was derived using the NPV described in Equation 7.

$$Post-screening\ point\ prevalence\ per\ 100{,}000\ population = (1-NPV)100{,}000 \tag{7}$$

Model calibration results can be found in the Supplementary Tables A.1 and A.2.

### Screening strategy analysis

We evaluated a combination of screening strategies with the model described above using the values in Table 2 to assess screening sensitivity of passengers travelling from a country with high COVID-19 disease point-prevalence (1,050 infections per 100,000 population). We visually represented several combinations of screening strategies used by international governments in their effectiveness at reducing translocation risk (refer to figures here for the visual representation). Using the screening strategies from Table 2, approximately 1.5 million different screening strategy combinations were then used to estimate the importance of each screening strategy (number of screening elements used in the strategy combinations are presented in the Supplementary Table A.3).

Data were split into training and test data sets for model validation, where 70% of the data were used in the training data set and 30% in the test data set. A generalized boosted regression model (gbm) was fitted to the training data, with sensitivity as the response variable and each screening strategy element as explanatory variables. Variable importance results from this gbm were used to assess the relative importance of each screening strategy element on screening sensitivity. The goodness of fit of the model was evaluated using the square of the correlation between the observed and predicted sensitivity in the testing data set (Equation 8) where $y_i$, the observed sensitivity; $\hat{y}_i$, predicted sensitivity; and $\bar{y}_i$, the mean predicted sensitivity.

$$R^2 = 1 - \frac{\sum_i (y_i - \hat{y}_i)^2}{\sum_i (y_i - \bar{y}_i)^2} \tag{8}$$

### Variability analysis

Screening sensitivity estimates based on the simulated passenger data set are treated as fixed values. To analyse the uncertainties around these screening sensitivity estimates, we generate a series of post-arrival testing scenarios using combinations of dual test strategies which include dual antigen, dual RT-PCR, RT-PCR followed by antigen, and antigen followed by RT-PCR tests. We then carry out Monte Carlo-based simulations as described in the above for a total of 10,000 passengers over a generalized flight lasting four hours each for 400 combinations of varying time to event parameters and symptomatic proportions for the different test strategies with varying difference of time (in days) between first and second test. The input parameter values include a combination of random draws from a beta distribution for PCR sensitivity, antigen specificity, symptomatic proportions for severely infected and asymptomatic passengers and from a gamma distribution for incubation period, and time to severe symptoms from the day of start of symptoms. The uncertainty in the sensitivity of the screening strategies and scenarios is measured in terms of the standard deviation on a logit scale. We then study the relationship between this variability in dual testing scenarios when observed against the difference in time (in days) that the two tests are undertaken.

Statistical analyses were all performed in R (version 4.0.3, www.r.project.org) [39], using packages 'covid19.analytics' (version 4.0.5), 'dplyr' (version 1.0.9), 'tidyr' (version 1.2.0), 'purrr' (version 0.3.4), 'forcats' (version 0.5.1), 'gbm' (version 2.1.8), and 'pracma' (version 2.3.8) [18, 40–45].

**Table 2.** Screening strategy values used to simulate different screening methods

| Screening strategy | Value |
|---|---|
| Quarantine (days) | 7, 10, 14 |
| Quarantine compliance (%) | 0, 25, 50, 75, 100 |
| Diagnostic test type | None, RT-PCR, Antigen |
| Number of diagnostic tests (*n*) | 0, 1, 2 |
| Diagnostic test timing | Pre-departure, Post-arrival |
| Pre-departure diagnostic testing (days) | 0, 2, 4, 7, 10, 14 |
| Post-arrival diagnostic testing (days) | 0, 2, 4, 7, 10, 14 |

Note that all post-arrival diagnostic testing scenarios assumes a quarantine length to the completion of the post-arrival test.

## Results

Seven commonly used passenger screening methods and their reduction of COVID-19 translocation from an origin destination with a high point-prevalence are presented in Figure 1. Among these seven common strategies, a combination of pre-departure and post-arrival testing, and greater quarantine length and compliance reduced translocation prevalence the greatest (Figure 1).

Among the screening strategies, the five most important factors in predicting sensitivity were: the number of days between arrival and a passenger first and second post-arrival test, quarantine compliance, the type of the first and second post-arrival test (Table 3). Interestingly, quarantine length, while important, was not ranked among the five most important factors in improving screening sensitivity (Table 3). Moreover, the type of pre-departure test (either first or second pre-departure test) added little additional value in predicting screening sensitivity. The validation of these results on the testing data showed strong agreement in the generalized boosted regression model being able to accurately identify testing sensitivity ($R^2$ = 0.98).

Variability in screening sensitivity had an inverse relationship with the mean screening sensitivity from all testing scenarios, where variability generally decreased with an increase in the mean sensitivity of antigen and RT-PCR testing (Figure 2). Among antigen and RT-PCR testing screening strategies, the most variability is observed when first and second tests are conducted closer (in days) to each other and with the variability decreasing with longer times between the first and second tests (Figure 2). Among the post-arrival testing scenarios, scenarios that included at least one RT-PCR had the greatest mean testing sensitivity, while scenarios that used dual antigen testing had the lowest sensitivity, requiring longer periods between the first and second post-arrival tests to have similar testing sensitivities to that of scenarios what included an RT-PCR test (Figure 2).

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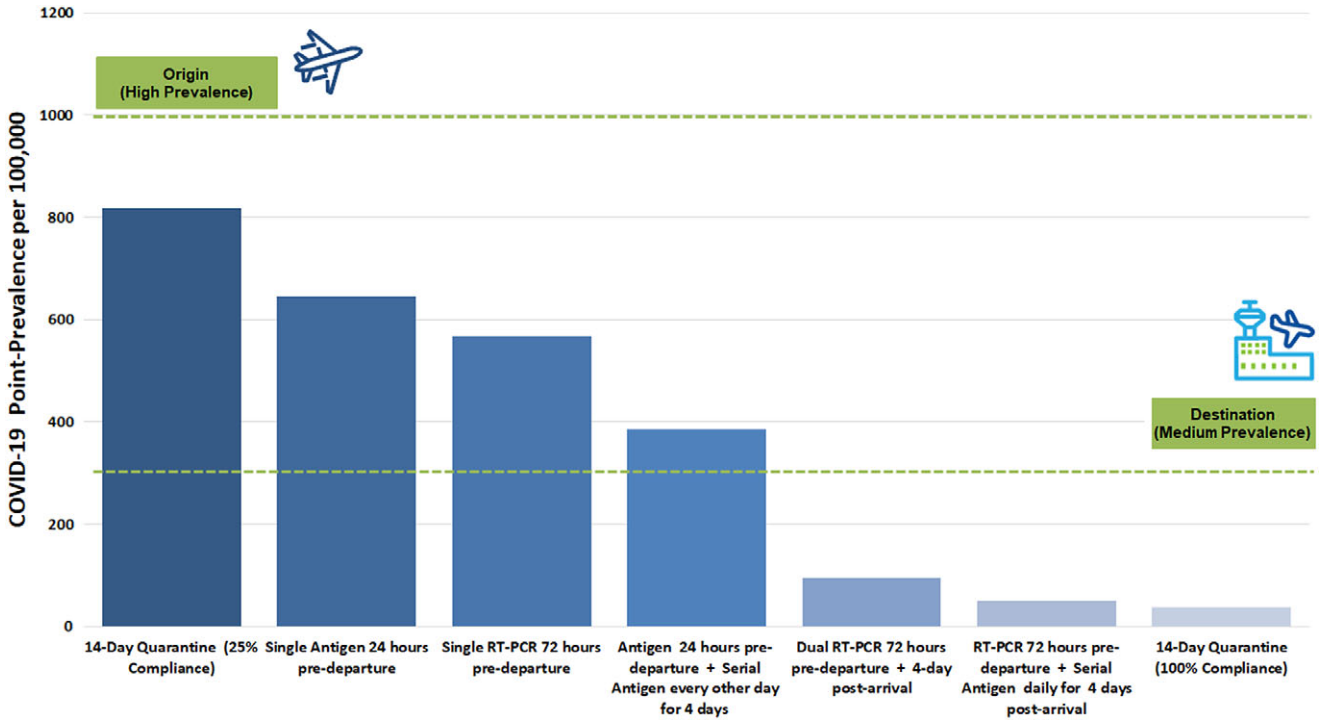


**Figure 1.** Reduction in point-prevalence from a destination with a high point-prevalence across different independent screening strategies ordered left to right by the least to greatest reduction in prevalence.

**Table 3.** Ranked relative variable importance

| Variable | Relative importance |
|---|---|
| Post-arrival 1st test day (*n*) | 34.00 |
| Quarantine compliance (%) | 22.29 |
| Post-arrival 2nd test day (*n*) | 12.79 |
| Post-arrival 1st test type | 12.01 |
| Post-arrival 2nd test type | 7.71 |
| Pre-departure 1st test day (*n*) | 4.54 |
| Pre-departure 2nd test day (*n*) | 4.32 |
| Quarantine length days (*n*) | 1.67 |
| Pre-departure 2nd test type | 0.35 |
| Pre-departure 1st test type | 0.32 |

## Discussion

Emerging and resurging infectious diseases pose a significant challenge to public health, and the prevention of the translocation of these diseases can benefit population health, economies, and society [46]. The COVID-19 pandemic has highlighted the translocation risk of infectious diseases by international and domestic travellers and the importance of effective screening practices, i.e., diagnostic testing, contact tracing, and quarantine [7, 47, 48]. However, not all screening practices are feasible, effective, sustainable, or necessary, depending on epidemiological context and differential prevalence of the disease between geographic areas [48]. Although screening is known to be effective, how that effectiveness (measured in terms of sensitivity, i.e., the true-positive proportion of true infections that test positive) varies by test type, test timing, combinations, pairing with quarantine, and underlying epidemiological conditions was previously unknown. Here, we address this gap by evaluating the importance of differing screening strategies and their variability in the sensitivity of screening passengers for COVID-19. We determine the importance of differing screening strategies when considering various testing regimes and quarantine (including length and compliance).

Important in the control and prevention of spreading infectious diseases is having detailed understandings of how mitigation strategies affect the risk of disease translocation between two locations. This fundamental knowledge allows mitigation strategies to adapt throughout public health emergencies and helps governments make informed decisions. For instance, passenger screening may not be necessary when two countries have similar incidence of disease, especially if their shared incidence is low [49]. Safely reducing the rigour of screening methods can reduce the burden on both public resources and travellers. However, this must be done with caution given the pace of emerging variants of SARS-CoV-2, their capacity for immune escape, and waning immunity from both vaccines and prior infection [50, 51]. Moreover, reduced screening may not be practical in areas where vaccination is low or undocumented. Screening and public health measures must adapt to the changing epidemiological situation to reduce disease risk with emerging immune-evading variants of COVID-19 [52].

Quarantine and pre-departure and post-arrival testing have been the main strategies used throughout the COVID-19 pandemic by governments to prevent the introduction of COVID-19 into communities [48]. We found that screening passengers with one or more post-arrival tests and quarantine compliance to be the most important factors predicting screening sensitivity. Interestingly, among the pre-departure testing factors, the timing of the first and second pre-departure test had a greater relative influence on screening sensitivity than the type of test given. While quarantine

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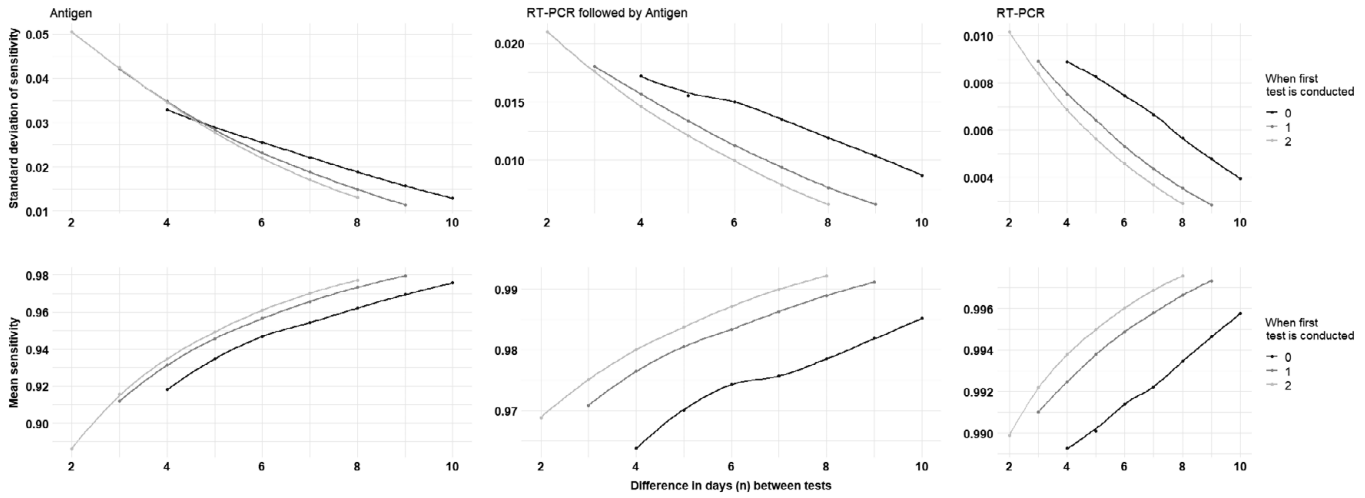


**Figure 2.** Relationship between the standard deviation of testing sensitivity (a) and mean sensitivity (b) in dual testing scenarios (on the y-axis) for simulation when both tests were carried out on the day of arrival or post-arrival and the number of days between the first and second test on the x-axis.

duration had a lower relative importance, it should be noted that quarantine is assumed to occur in screening strategies that involve post-arrival testing, and therefore, its importance is likely also reflected in post-arrival testing factors. Our model showed that quarantine duration can be shortened when combined with post-arrival testing while achieving similar screening sensitivity and disease translocation. For instance, we show that a combination of pre- and post-departure/arrival testing with a four-day post-arrival quarantine can provide a similar reduction in translocation prevalence than that of a scenario with a 14-day quarantine with complete quarantine compliance. These findings align with modelling on the translocation risk in COVID-19-free countries, where a combination of testing and post-arrival quarantine was found to be the most effective prevention in New Zealand [49]. Among screening strategies, there are certain combinations that may have similar reductions in translocation prevalence. For instance, we show in Figure 1 that a single 24-h pre-departure antigen test verses a single 72-h pre-departure RT-PCR test (Figure 1) can have comparable translocation reductions. It is therefore likely that health bodies may be able to tailor the combination of screening factors to suit public health logistics and objectives (i.e., lowering prevalence to a specific level, or detection of a percentage of infectious persons) that balance economic costs and incomitances to travellers. COVID-19 screening has been deployed in other settings, such as in schools and summer camps, and has been shown to reduce infection rates [53]. Moreover, weekly screening of healthcare workers and other high-risk groups by the use of RT-PCR testing was estimated to reduce their contribution to SARS-CoV-2 transmission by 23% [54]. Serial pre-departure testing may help to reduce disease translocation and the risk of transmission during air travel; however, a drawback of multiple serial testing is the increased rate of false-positive tests. For example, with a specificity of 99%, conducting two tests instead of one test approximately doubles the false-positive rate from 1% to 2%, and additional testing increases the false-positive rate for the test series even further (to approximately 10% for 10 tests, for example). While 99% specificity could be a conservative estimate for RT-PCR tests for COVID-19, it is difficult to determine since RT-PCR positive is often considered the gold standard for COVID-19 infection despite a possible lack of relevance to contagiousness. Nonetheless, the false-positive concern could become even more problematic for technologies with lower specificity values than RT-PCR [55]. Complicating these factors and test relevance is that while RT-PCR screens can detect the lowest levels of viral presence, antigen testing is the better tool for discovering contagiousness, which is arguably the most important variable to uncover for travel risk [56].

Ideally, antigen and RT-PCR screening is performed during pre-departure as close to the time of departure as possible, so that disease transmission risk is reduced as far upstream in the travel journey as possible and fewer early-stage infections are missed by the testing. However, the turn-around time for RT-PCR results may not support testing sufficiently close to departure. By contrast, COVID-19 antigen tests take 15 min to generate results, are less expensive than RT-PCR, and do not require instrumentation for analysis. Combination of screening approaches, especially those that include antigen tests, has allowed governments to shorten and/or remove quarantine periods for travellers from countries with high COVID-19 prevalence [57]. We find that the variability in testing sensitivity is reduced and testing sensitivity increases with a greater time between the first and second post-arrival RT-PCR and antigen (and a combination of both) tests. Dual antigen tests were found to have the greatest relative increase in testing sensitivity and decrease in test variability than compared with other scenarios that combine RT-PCR with antigen tests and dual RT-PCR post-arrival testing. However, relative variance in testing sensitivity was smallest in testing scenarios that use dual RT-PCR tests. If screening strategies were to rely upon dual antigen screening, we find, to minimize the variability in screening sensitivity and maximize the number of infectious individuals identified, a second post-arrival antigen test can improve testing sensitivity by 8 % when tested 6 days apart. Based on these findings, two antigen tests can be used in screening with less cost and inconvenience to travellers than several RT-PCR tests or a combination of both and still achieve comparable detection of infectious persons. By knowing the characteristics that influence the sensitivity of detecting infectious individuals, screening strategies can be optimized to develop a combination that best suits a nations healthcare capacity. For instance, if pathology services are not able to meet the demand for RT-PCR testing, knowing how testing sensitivity increases with multiple antigen tests over several days can relieve stress on healthcare systems while maintaining the same reduction in translocation

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risk. Despite the potential for infected passengers to enter the air travel system, the aviation industry has shown that, while on the aircraft, transmission risk of COVID-19 and other respiratory infections (i.e., Swine Flu) remains relatively low [58, 59]. Moreover, public health initiatives in aviation have helped to improve public confidence in their safety during travel [60]. Therefore, screening has the greatest impact on public health when used in limiting the risk of the translocation of diseases.

## Limitations

COVID-19 has challenged public health management strategies with its pre-symptomatic infectiousness and rapid evolution of new variants [61]. These variants have affected vaccine efficacy, transmissibility, and infection severity. Thus, a limitation of our work is that disease transmission and infection severity were not assessed here. However, our model can indirectly analyse vaccine efficacy and waning population immunity by assuming a set vaccine efficacy value and vaccine coverage for the departure country. We further do not account for varying levels of vaccine status (i.e., first, second, and booster doses), nor various vaccine brands. Instead, we make the general assumption of a standard vaccination efficacy and coverage across the entire population. By doing so, it is possible to evaluate translocation risk over various scenarios as vaccination programmes progress and evolve. Furthermore, our model assumes the same disease timeline was used for vaccinated and unvaccinated passengers. Even though there are some studies that suggest the disease timeline differs and is shortened for vaccinated individuals [30], the Centers for Disease Control and Prevention [62] recommends the same quarantine and masking guidelines for individuals that test positive for COVID-19, regardless of vaccination status. Consequently, this study uses the same timeline for all travellers, regardless of vaccination status, to create a conservative estimate of the impact of using reduced testing for vaccinated individuals.

## Conclusion

Significant barrier for public health, the travelling public, and for the aviation industry include lack of consistency in screening approaches across the globe and rapidly evolving knowledge about COVID-19 as a disease. Here, we show the importance of various passenger disease screening measures used in air travel with identifying individuals infected with COVID-19. We find that post-arrival testing and quarantine compliance to be the more important factors in screening. Moreover, shorter quarantine periods coupled with testing can be effective in reducing the length of quarantine periods, lessening the burden and economic cost to the travelling public. RT-PCR testing can be costly and onerous to individuals and to public health services; here, we show that antigen testing, being cheaper and quicker for diagnosis, is equally as affective at detecting those infected with COVID-19 offering a less burdensome approach to passenger screening. Clear quantification of the effectiveness of various screening strategies not only benefits governments seeking to keep their populations safe, but also increases passenger confidence, provides objective guidelines that can inform the standardization of policies across jurisdictions, and reduces burden to public health and economies by minimizing quarantine durations. Governments have recently sought to improve future pandemic preparedness, such as the establishment of the Australian Centres for Disease Control and Prevention and the US legislation for the National Aviation Preparedness Plan for pandemics; the model we have developed here provides a flexible framework to evaluate a wide array of screening strategies and can be easily adapted to other existing or emerging diseases aiding in future policy development.

**Supplementary material.** The supplementary material for this article can be found at https://doi.org/10.1017/S0950268824000220.

**Data availability statement.** Details of the model, data sources & availability, and other assumptions are provided in the Methods section.

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## References

[1] **Air Transport Bureau** (2022) Effects of Novel Coronavirus (COVID-19) on Civil Aviation: Economic Impact Analysis. International Civil Aviation Organization.
[2] **Tabares DA** (2021) An airport operations proposal for a pandemic-free air travel. *Journal of Air Transport Management* **90**, 101943.
[3] **Bielecki M**, et al. (2021) Air travel and COVID-19 prevention in the pandemic and peri-pandemic period: A narrative review. *Travel Medicine and Infectious Disease* **39**, 101915.
[4] **Russell TW**, et al. (2021) Effect of internationally imported cases on internal spread of COVID-19: A mathematical modelling study. *The Lancet Public Health* **6**, e12–e20.
[5] **Sun X**, **Wandelt S and Zhang A** (2021) Delayed reaction towards emerging COVID-19 variants of concern: Does history repeat itself? *Transportation Research Part A: Policy and Practice* **152**, 203–215.
[6] **de La Vega M-A** (2022) *Et al.* SARS-CoV-2 molecular diagnosis at airports to minimize travel-related COVID-19 spread. *Scientific Reports* **12**, 11753.
[7] **Movsisyan A**, et al. (2021) Travel-related control measures to contain the COVID-19 pandemic: An evidence map. *BMJ Open* **11**, e041619.
[8] **Larremore DB**, et al. (2021) Test sensitivity is secondary to frequency and turnaround time for COVID-19 screening. *Science Advances* **7**, eabd5393.
[9] **Bielecki M**, et al. (2020) Reprint of: Air travel and COVID-19 prevention in the pandemic and peri-pandemic period: A narrative review. *Travel Medicine and Infectious Disease* **38**, 101939.
[10] **Dollard P**, et al. (2020) Risk assessment and management of COVID-19 among travelers arriving at designated US airports, January 17–September 13, 2020. *Morbidity and Mortality Weekly Report* **69**, 1681.
[11] **Shortall R**, **Mouter N and Van Wee B** (2021) COVID-19 passenger transport measures and their impacts. *Transport Reviews* **42**, 441–466.
[12] **Tande AJ**, et al. (2021) SARS-CoV-2 testing before international airline travel, December 2020 to May 2021. *Mayo Clinic Proceedings* **96**, 2856–2860.
[13] **Le Targa L**, et al. (2022) SARS-CoV-2 testing of aircraft wastewater shows that mandatory tests and vaccination pass before boarding did not prevent massive importation of omicron variant into Europe. *Viruses* **14**, 1511.
[14] **Johansson MA**, et al. (2021) Reducing travel-related SARS-CoV-2 transmission with layered mitigation measures: Symptom monitoring, quarantine, and testing. *BMC Medicine* **19**, 1–13.
[15] **de Figueiredo A**, **Larson HJ and Reicher S** (2021) The potential impact of vaccine passports on inclination to accept COVID-19 vaccinations in the

United Kingdom: Evidence from a large cross-sectional survey and modelling study. *EClinicalMedicine* **40**, 101109.
[16] **Larsen R** (2022) H.R.884 National Aviation Preparedness Plan Act of 2022. H. Rept. 117–458.
[17] **Dong E, Du H and Gardner L** (2020) An interactive web-based dashboard to track COVID-19 in real time. *The Lancet Infectious Diseases* **20**, 533–534.
[18] **Ponce M and Sandhel A** (2021) covid19.analytics: An R package to obtain, analyze and visualize data from the coronavirus disease pandemic. *Journal of Open Source Software* **6**, 2995.
[19] **Directorate of Health and the Department of Civil Protection and Emergency Management of Iceland. COVID-19 in Iceland – Statistics** (2020). Available at https://www.covid.is/data (accessed 9 December 2020).
[20] **Smieja M**, et al. (2020) Canadian International COVID-19 Surveillance Border Study: Interim Results Backgrounder. McMaster HealthLabs. Available at https://www.aci-europe.org/downloads/resources/MHL%20Border%20Study%20Backgrounder.pdf (accessed 9 December 2020)
[21] **Goel V**, et al. (2021) COVID-19 international border surveillance at Toronto's Pearson Airport: A cohort study. *BMJ Open* **11**, e050714.
[22] **Prince-Guerra JL**, et al. (2021) Evaluation of Abbott BinaxNOW rapid antigen test for SARS-CoV-2 infection at two community-based testing sites — Pima County, Arizona, November 3–17, 2020. *MMWR. Morbidity and Mortality Weekly Report* **70**, 100–105.
[23] **Pollock NR**, et al. (2021) Performance and implementation evaluation of the Abbott BinaxNOW rapid antigen test in a high-throughput drive-through community testing site in Massachusetts. *Journal of Clinical Microbiology* **59**, 10.
[24] **Pilarowski G**, et al. (2021) Field performance and public health response using the BinaxNOWTM rapid severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) antigen detection assay during community-based testing. *Clinical Infectious Diseases* **73**, e3098–e3101.
[25] **Institute for Health Metrics and Evaluation** (2022) *COVID-19 vaccine efficacy summary*. Available at https://www.healthdata.org/covid/covid-19-vaccine-efficacy-summary (accessed 12 September 2022).
[26] **Quilty BJ**, et al. Effectiveness of airport screening at detecting travellers infected with novel coronavirus (2019-nCoV). *Eurosurveillance* **25**, 2000080. https://doi.org/10.2807/1560-7917.ES.2020.25.5.2000080.
[27] **Joung SY**, et al. (2022) Awareness of SARS-CoV-2 omicron variant infection among adults with recent COVID-19 Seropositivity. *JAMA Network Open* **5**, e2227241.
[28] **Shang W**, et al. (2022) Percentage of asymptomatic infections among SARS-CoV-2 omicron variant-positive individuals: A systematic review and meta-analysis. *Vaccine* **10**, 1049.
[29] **Lewnard JA**, et al. (2022) Clinical outcomes associated with SARS-CoV-2 omicron (B.1.1.529) variant and BA.1/BA.1.1 or BA.2 subvariant infection in Southern California. *Nature Medicine* **28**, 1933–1943.
[30] **Ronchini C**, et al. (2022) Lower probability and shorter duration of infections after COVID-19 vaccine correlate with anti-SARS-CoV-2 circulating IgGs. *PloS One* **17**, e0263014.
[31] **Centers for Disease Control and Prevention** (2022) *Isolation and Precautions for People with COVID-19*. Available at https://www.cdc.gov/coronavirus/2019-ncov/your-health/isolation.html?CDC_AA_refVal=https%3A%2F%2Fwww.cdc.gov%2Fcoronavirus%2F2019-ncov%2Fyour-health%2Fquarantine-isolation.html (accessed 16 August 2022).
[32] **Centers for Disease Control and Prevention** (2022) *Testing Strategies for SARS-CoV-2*. Available at https://www.cdc.gov/coronavirus/2019-ncov/lab/resources/sars-cov2-testing-strategies.html (accessed 16 August 2022).
[33] **Bullard J**, et al. (2020) Predicting infectious severe acute respiratory syndrome coronavirus 2 from diagnostic samples. *Clinical Infectious Diseases* **71**, 2663–2666.
[34] **Park M**, et al. (2021) Determining the communicable period of SARS-CoV-2: A rapid review of the literature, March to September 2020. *Eurosurveillance* **26**, 2001506.
[35] **Guglielmi G** (2020) Fast Coronavirus tests: What they can and can't do. *Nature* **585**, 496–499.
[36] **Sethuraman N, Jeremiah SS and Ryo A** (2020) Interpreting diagnostic tests for SARS-CoV-2. *JAMA* **323**, 2249.
[37] **Monaghan TF**, et al. (2021) Foundational statistical principles in medical research: Sensitivity, specificity, positive predictive value, and negative predictive value. *Medicina* **57**, 503.
[38] **Singanayagam A**, et al. (2020) Duration of infectiousness and correlation with RT-PCR cycle threshold values in cases of COVID-19, England, January to May 2020. *Eurosurveillance* **25**, 2001483. https://doi.org/10.2807/1560-7917.ES.2020.25.32.2001483.
[39] **R Core Team** (2020) *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. Available at: http://www.R-project.org/
[40] **Wickham H**, et al. (2022) *dplyr: A grammar of data manipulation. R package version 1.0.9.*
[41] **Wickham H and Henry L** (2022) *tidyr: Tidy messy data. R package version 1.2.0.*
[42] **Henry L and Wickham H** (2020) *Purrr: Functional programming tools. R package version 0.3.4.*
[43] **Wickham H** (2021) *Forcats: Tools for working with categorical variables (factors). R package version 0.5.1.*
[44] **Borchers HW** (2022) *Pracma: Practical numerical math functions. R package version 2.3.8.*
[45] **Greenwell B, Boehmke B and Cunningham J** (2021) *gbm: Generalized boosted regression models. R package version 2.1.8.* Available at https://CRAN.R-project.org/package=gbm (accessed 16 August 2022).
[46] **Grobusch MP**, et al. (2021) Travel-related infections presenting in Europe: A 20-year analysis of EuroTravNet surveillance data. *The Lancet Regional Health - Europe* **1**, 100001.
[47] **Grépin KA**, et al. (2021) Evidence of the effectiveness of travel-related measures during the early phase of the COVID-19 pandemic: A rapid systematic review. *BMJ Global Health* **6**, e004537.
[48] **Burns J**, et al. (2021) International travel-related control measures to contain the COVID-19 pandemic: A rapid review. *Cochrane Database of Systematic Reviews* **3**, 269.
[49] **Wilson N**, et al. (2021) Estimating the impact of control measures to prevent outbreaks of COVID-19 associated with air travel into a COVID-19-free country. *Scientific Reports* **11**, 10766.
[50] **Grant R**, et al. (2022) Impact of SARS-CoV-2 Delta variant on incubation, transmission settings and vaccine effectiveness: Results from a nationwide case-control study in France. *The Lancet Regional Health - Europe* **13**, 100278.
[51] **Tartof SY**, et al. (2022) Durability of BNT162b2 vaccine against hospital and emergency department admissions due to the omicron and delta variants in a large health system in the USA: A test-negative case–control study. *The Lancet Respiratory Medicine* **10**, 689–699.
[52] **Le Rutte EA**, et al. (2022) Modelling the impact of omicron and emerging variants on SARS-CoV-2 transmission and public health burden. *Communications Medicine* **2**, 93.
[53] **Blaisdell LL**, et al. (2020) Preventing and mitigating SARS-CoV-2 transmission—Four overnight camps, Maine, June–August 2020. *Morbidity and Mortality Weekly Report* **69**, 1216.
[54] **Grassly NC**, et al. (2020) Comparison of molecular testing strategies for COVID-19 control: A mathematical modelling study. *The Lancet Infectious Diseases* **20**, 1381–1389.
[55] **Chen LH and Steffen R** (2021) SARS-CoV-2 testing to assure safety in air travel. *Journal of Travel Medicine* **28**, taaa241.
[56] **Routsias JG**, et al. (2021) Diagnostic performance of rapid antigen tests (RATs) for SARS-CoV-2 and their efficacy in monitoring the infectiousness of COVID-19 patients. *Scientific Reports* **11**, 22863.
[57] **Wells CR**, et al. (2022) Quarantine and testing strategies to ameliorate transmission due to travel during the COVID-19 pandemic: A modelling study. *The Lancet Regional Health - Europe* **14**, 100304.
[58] **Trent S**, et al. (2022) Inhaled mass and particle removal dynamics in commercial buildings and aircraft cabins. *Ashrae* **64**, 10–21.
[59] **Silcott D**, et al. (2020) TRANSCOM/AMC Commercial Aircraft Cabin Aerosol Dispersion Tests. United States Transportation Command & Air Mobility Command. Available at https://www.ustranscom.mil/cmd/docs/TRANSCOM%20Report%20Final.pdf (accessed 2 August 2022).
[60] **Boeing** (2022) *Travel Confidently with Boeing*. Available at https://www.boeing.com/confident-travel/ (accessed 2 August 2022).
[61] **Hadj Hassine I** (2022) Covid-19 vaccines and variants of concern: A review. *Reviews in Medical Virology* **32**. https://doi.org/10.1002/rmv.2313.
[62] **Centres for Disease Control and Prevention (CDC)** (2022) *Quarantine and Isolation*. Available at https://www.cdc.gov/coronavirus/2019-ncov/your-health/quarantine-isolation.html (accessed 2 August 2022).

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