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Citation for published version:

Digital Object Identifier (DOI):
10.1016/S2589-7500(22)00093-0

Link:
Link to publication record in Edinburgh Research Explorer

Document Version:
Publisher's PDF, also known as Version of record

Published In:
The Lancet Digital Health

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Prediction of hospital-onset COVID-19 infections using dynamic networks of patient contact: an international retrospective cohort study

Ashleigh Myall, James R Price, Robert L Peach, Mohamed Abbas, Sid Mookerjee, Nina Zhu, Isa Ahmad, Damien Ming, Farzan Ramzan, Daniel Teixeira, Christophe Graf, Andrea Y Weiße, Stephan Harbarth, Alison Holmes, Mauricio Barahona

**Summary**

**Background** Real-time prediction is key to prevention and control of infections associated with health-care settings. Contacts enable spread of many infections, yet most risk prediction frameworks fail to account for their dynamics. We developed, tested, and internationally validated a real-time machine-learning framework, incorporating dynamic patient-contact networks to predict hospital-onset COVID-19 infections (HOCIs) at the individual level.

**Methods** We report an international retrospective cohort study of our framework, which extracted patient-contact networks from routine hospital data and combined network-derived variables with clinical and contextual information to predict individual infection risk. We trained and tested the framework on HOCIs using the data from 51157 hospital inpatients admitted to a UK National Health Service hospital group (Imperial College Healthcare NHS Trust) between April 1, 2020, and April 1, 2021, intersecting the first two COVID-19 surges. We validated the framework using data from a Swiss hospital group (Department of Rehabilitation, Geneva University Hospitals) during a COVID-19 surge (from March 1 to May 31, 2020; 40057 inpatients) and from the same UK group after COVID-19 surges (from April 2 to Aug 13, 2021; 43375 inpatients). All inpatients with a bed allocation during the study periods were included in the computation of network-derived and contextual variables. In predicting patient-level HOCI risk, only inpatients spending 3 or more days in hospital during the study period were examined for HOCI acquisition risk.

**Findings** The framework was highly predictive across test data with all variable types (area under the curve [AUC]-receiver operating characteristic curve [ROC] 0·89 [95% CI 0·88–0·90]) and similarly predictive using only contact-network variables (0·88 [0·86–0·90]). Prediction was reduced when using only hospital contextual (AUC-ROC 0·82 [95% CI 0·80–0·84]) or patient clinical (0·64 [0·62–0·66]) variables. A model with only three variables (ie, network closeness, direct contacts with infectious patients [network derived], and hospital COVID-19 prevalence [hospital contextual]) achieved AUC-ROC 0·85 (95% CI 0·82–0·88). Incorporating contact-network variables improved performance across both validation datasets (AUC-ROC in the Geneva dataset increased from 0·84 [95% CI 0·82–0·86] to 0·88 [0·86–0·90]; AUC-ROC in the UK post-surge dataset increased from 0·49 [0·46–0·52] to 0·68 [0·64–0·70]).

**Interpretation** Dynamic contact networks are robust predictors of individual patient risk of HOCIs. Their integration in clinical care could enhance individualised infection prevention and early diagnosis of COVID-19 and other nosocomial infections.

**Funding** Medical Research Foundation, WHO, Engineering and Physical Sciences Research Council, National Institute for Health Research (NIHR), Swiss National Science Foundation, and German Research Foundation.

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Research in context

Evidence before this study

Throughout the COVID-19 pandemic, health-care facilities have had considerable numbers of hospital-onset COVID-19 infections (HOCl’s). Despite substantially higher rates of COVID-19 morbidity and mortality among hospitalised patients, predictive models of HOCl are yet to be fully used in health-care settings. To address this gap, we have designed a machine-learning framework that integrates dynamic patient contact-networks with traditional patient clinical risk factors and contextual hospital variables. Patient contact networks are a natural approach to model the contact-mediated transmission of COVID-19 and other infectious diseases. Our study investigates the use of contact-network variables in predicting HOCl’s at the patient level and their generalisability to various hospital settings. We performed two searches on PubMed (Sept 22, 2021) for English-language articles. Search one was on prediction of HOCl’s, using the search terms “hospital-onset COVID-19 infections”, “nosocomial COVID-19”, “prediction”, and “forecasting”; search two was on the use of contact-networks for prediction of infections acquired in health-care settings, based on the search terms “healthcare-acquired infections”, “nosocomial infections”, “prediction”, “forecasting”, “contact networks”, and “dynamic contact networks”. Search one identified no studies performing a comprehensive investigation into risk factors of HOCl at the patient level. Although several works examined HOCl epidemiology, providing characterisation of contacts, these studies were performed at single hospital sites, with few patients, and did not include a risk-factor analysis. Other studies examined risk factors for predicting patient risk of COVID-19 on hospital admission; however, by definition, these studies target only community-onset COVID-19 infections and not HOCl’s and thus do not capture the in-hospital sources of exposure risk. Search two identified studies that used the total number of patient contacts or the total number of contacts with infectious cases. However, no studies of infections acquired in health-care settings incorporated contact connectivity beyond a patient’s immediate contacts to predict infection risk. Furthermore, the studies found in our searches did not use sophisticated network-theoretical measures or modelling techniques to predict individual patient risk, nor did they account for the time-varying nature of the contacts.

Added value of this study

To our knowledge, this is the first study to forecast HOCl’s at the patient level by constructing contact-networks from routinely collected hospital bed records. To investigate the predictive use of patient contact-networks, we used a large multinational hospital dataset collected throughout extended periods of the COVID-19 pandemic in two hospital groups; one in London, UK, and one in Geneva, Switzerland. Using these datasets, we constructed and generalised models to predict HOCl’s at the patient level both with and without measures of patient centrality calculated using the dynamic patient contact-networks. Our results show that variables extracted from patient contact-networks are strong predictors of HOCl in both testing and validation. Such network measures lead to improved prediction over standard risk-factor models on the basis of patient clinical data or hospital contextual variables. Most network-derived variables were significantly elevated in HOCl’s, emphasising their importance as risk factors.

Implications of all the available evidence

This study shows that dynamic contact-networks provide novel sources of predictive power for respiratory infections acquired in health-care settings, improving the performance of traditional risk-factor prediction models for HOCl’s. Contact-network-derived risk factors have the potential to enhance individualised infection prevention and early diagnosis. We designed a machine-learning framework to extract contact risk factors using routinely available bed administrative data and showed its novel and generalisable prediction power. The framework can be used in real time to generate daily risk predictions as part of a suite of surveillance tools in modern, data-driven infection prevention and control strategies.

spreading by interrupting transmission chains.7 Contact tracing of infected patients is effective at identifying disease super-spreaders,9 who are strong HOCl drivers,10 and secondary cases and has played a pivotal role in national COVID-19 responses.11–13 However, exploiting the entire contact network, rather than direct contacts to individuals with known infection alone, provides greater information to characterise transmission.14 Indeed, early in the COVID-19 pandemic, population mobility and interactions guided national policy to reduce transmission.20 In health-care settings, the overall number of direct contacts of a patient is predictive of HCAI.21–23 Yet, these studies24–26 fail to use the full dynamic information of contacts.27

In this study, we combine dynamic networks of patient contacts (based on bed allocation records) with clinical attributes and hospital contextual data into a novel forecasting framework to predict patient risk of HOCl acquisition for targeting preventive interventions. As a proof of principle, we perform a retrospective cohort study to assess the predictive power of risk factors that were extracted from patient-contact networks, constructed from routinely collected hospital data. We train and test models on a large London hospital dataset spanning the first two major UK surges of COVID-19 (ie, March 23–May 30, 2020 and Sept 7, 2020–April 24, 2021). We then validate the predictive gain from contact-network risk factors by applying the framework to an external dataset from a university-affiliated geriatric hospital in Geneva during surge one (ie, March 1–May 31, 2020) and to data from the same
London hospital group after surge two (ie, after April 2–Aug 13, 2021) in the UK, when COVID-19 had become endemic.

Methods
Study design and participants
This international retrospective cohort study consists of a complete case analysis including all hospital inpatients with bed allocations. For training and testing we used data from a large London hospital group (Imperial College Healthcare NHS trust) (with approximately 1200 inpatient beds across five sites) from April 1, 2020, to April 1, 2021, capturing the UK’s first surge (ie, March 23–May 30, 2020) and second surge (ie, Sept 7, 2020–April 24, 2021; appendix p 2). For validation, we applied the framework to a non-UK hospital group in the Department of Rehabilitation and Geriatrics, Geneva University Hospitals, Geneva, Switzerland (with approximately 600 inpatient beds across three sites), during Switzerland’s first surge (ie, March 1–May 31, 2020), and to data from the same London hospital group after the second surge in the UK (ie, April 2–Aug 13, 2021). The infection prevention and control (IPC) measures are detailed in the appendix (p 2).

Patient data were extracted and de-identified by the business intelligence system (London), iCARE (London), and from in-house electronic health records (Geneva).

Inclusion criteria were any inpatient with an allocated bed during the study period. All inpatients were included in the formation of the dataset, whereas only patients...
Articles

Background hospital infections and contact structure across the study period

Daily number of new patients who tested positive for COVID-19 within the hospital (COCI and HOCI) varied substantially across the study period. A peak of 59 cases was reached on March 30, 2020, and a peak of 64 cases was reached on Jan 6, 2021, dipping to zero new daily cases over days during July, August, September, and October. The patient-contact network also varied across the study period, with differences in connectivity and size of patient-contact clusters between each of the infection surges and during the summer period. COCI=community-onset COVID-19 infection. HOCI=hospital-onset COVID-19 infection.

Figure 1: Background hospital infections and contact structure across the study period Daily new COVID-19 cases

<table>
<thead>
<tr>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>HOCI</td>
<td>0</td>
<td>14 HOCIs</td>
<td>18 HOCIs</td>
<td>0</td>
<td>64 new cases: (50 COCs) (14 HOCIs)</td>
<td>60 new cases: (50 COCs) (9 HOCIs)</td>
<td>0 new cases</td>
</tr>
<tr>
<td>COCI</td>
<td>14 HOCIs</td>
<td>18 HOCIs</td>
<td>0</td>
<td>64 new cases: (50 COCs) (14 HOCIs)</td>
<td>0 new cases</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Dynamic forecasting framework

We developed a framework to predict infections (appendix pp 2–6), enabling risk stratification, that combined dynamic patterns of contact, exposure to infection, and standard risk factors (R package). Fixed patient variables (eg, demographics) were collected, and dynamic, time-dependent variables (eg, contact-network graph-theoretical centrality for each patient and hospital contextual variables) were computed from a sliding time window to be used as model predictors over a forecasting horizon. In alignment with the maximum incubation period of COVID-19, we set the window length to 14 days and the forecasting horizon to 7 days.

For each time window, we extracted patient clinical variables, hospital contextual variables (relating to the hospital inpatient context), and contact-network variables (centrality measures) using network-theoretical analytics from each of the room, ward, and building contact networks derived from the data (panel; appendix pp 3–4).

Evaluation of machine learning models

We constructed and evaluated models to predict HOCI (appendix p 7), using a 70 to 30 training to testing data split (where 70% of patients were randomly selected and allocated to the training set, and the remaining 30% were allocated to the test set). Following an unbiased comparison (appendix p 7), we report results of the best machine learning model (eXtreme Gradient Boosting [XGBoost]).

Performance was measured by prediction on the test set, quantified by area under the receiver operating curve (AUC-ROC); balanced accuracy; sensitivity; specificity; and positive predictive values, negative predictive values, and positive and negative likelihood ratios, adjusted for multiple prediction bias (appendix p 7). To aid interpretation, we ranked variables by their predictive
contribution using a recursive elimination strategy (appendix p 8).

Two validation datasets were used: one external dataset from a non-UK hospital with three sites (ie, three sites of the Department of Rehabilitation and Geriatrics, Geneva University Hospitals, Geneva, Switzerland) collected during the first epidemic surge in Switzerland and one internal dataset from the same London hospital group from which data were initially collected after UK surges in COVID-19 was endemic. The same inclusion criteria were used for the training and testing dataset and the validation datasets (ie, all inpatients with a bed allocation during the dates of study were included in the formation of the dataset, whereas assignment of control and HOCI labels was restricted to patients who had spent 3 days or more in hospital).

To perform validation, we used the XGBoost model with hyper parameters optimised on the training data and then applied to the new data with available risk-factor variables. Due to the smaller size of the validation datasets compared with the test dataset, we report 5-fold cross validation performance.

**Statistical analysis**

Univariate variables analysis was performed to identify risk factors by comparing values between HOCI and control groups in patients who were in hospital for 3 days or more (appendix pp 2, 9). All inpatients with a bed allocation during the study periods were included in the computation of network-derived and contextual variables. In predicting patient-level HOCI risk, only inpatients spending 3 or more days in hospital during the study period were included. To establish significance, we used either Mann-Whitney U or χ² tests and report p values adjusted for length of patient stay in hospital (appendix p 5). Statistical analyses were done with R (version 4.0.4).

**Role of the funding source**

The funders of the study had no role in study design, data collection, data analysis, data interpretation, or writing of the report.

**Results**

A total of 51157 patients were admitted to the London hospital group during the study’s training and testing period (April 1, 2020–April 1, 2021). Of these patients, 3439 (6.7%) patients tested positive for SARS-CoV-2, including 2950 (5.8%) COCIs and 489 (1.0%) HOCIs (appendix p 9). Together, 21576 (42.2%) patients had stayed at least 3 days in hospital and were included in the forecasting data (489 HOCIs and 21087 non-HOCIs).

The prevalence of in-hospital COVID-19 cases had two surges congruent with national UK cases (figure 1). Surge one peaked on March 30, 2020 (ie, one day before the study period), at 59 new daily positive hospital cases (50 COCIs and nine HOCIs); surge two peaked on Jan 6, 2021, at 64 new daily cases (50 COCIs and 14 HOCIs). The two surges differed when analysing the time series (appendix p 10): the proportion of HOCIs was higher during surge two (17.8% HOCIs [406 of 2276 infections were HOCIs]) than during surge one (15.1% HOCIs [167 of 1107 infections were HOCIs]) and the correlation between HOCIs and COCIs was higher.
During surge two (R=0.79; p<0.0001) than during surge one (R=0.59; p<0.0001). The background variant makeup also varied between the UK surges, with the alpha (B.1.1.7) variant making up 59.3% and the delta (B.1.6172) variant making up 1%-1% of all nationally sequenced COVID-19 cases during surge two, whereas they were absent during surge one (appendix p 10).

The patient-contact network structure also varied throughout the pandemic (figure 1). The median number of contacts (degree) over networks across time was four in rooms (ie, the number of people sharing a room), 22 in wards (ie, the number of people sharing a ward), and 67 in buildings (ie, the number of people located in the same building at the same time), with an increasing trend over time (appendix p 12). Surge one had lower median degrees (three in rooms, 18 in wards, and 57 in buildings) than did surge two (four in rooms, 23 in wards, and 70 in buildings). Other network measures also varied over the study period (appendix p 12), with network metrics reflecting a denser contact-network in surge two than in surge one (figure 1).

Univariate analysis identified ten clinical variables that were differentially represented in patients with HOCI versus controls (table 1). Both age and gender identity were significantly different between patients with HOCI and controls, with HOCIs over-represented in older patients and those who identified as male. Regarding specialties, HOCIs were found in a higher proportion of patients in elderly care, general medicine, renal, and surgery compared with controls, and significantly lower proportions in patients from cardiology, gynaecology, obstetrics, and paediatrics.

Six of ten hospital contextual variables were significantly different between the HOCI and control groups (table 1). Relative to controls, patients with HOCI were associated with longer length of stay before testing positive and were in hospital during times of higher hospital-bed occupancy and during periods of increased background incidence of COVID-19. No significant difference between the HOCI and control groups was observed for variables related to movement rates (between beds, rooms, wards, and sites).

For network variables, 24 of 30 centrality measures were significantly higher in HOCI patients (eight of ten from each room-contact, ward-contact, and building-contact network; table 1). Network variables that were significantly higher in the HOCI group than in the control group across the three contact networks included measures accounting for infectious COVID-19 cases (ie, infected degree, infected degree centrality, and infected closeness centrality) and general network connectivity (ie, degree, closeness centrality, clustering coefficient, and K-core number).

We trained different models on our London data using sets of variables of different types (panel). All models had high predictive power (table 2; figure 2A, B). In particular, the model based solely on contact-network variables (AUC-ROC 0.88 [95% CI 0.86–0.90]) performed similarly to the model based on all variables (0.89 [0.88–0.90]) and yielded more predictive power than models using solely hospital context variables (0.82 [0.80–0.84]) or clinical variables (0.64 [0.62–0.66]). To ascertain the predictive power of different types of contacts, separate models were trained on variables from each of the three contact networks (ie, room, ward, and building). The model based on ward-contact network variables had the highest predictive power (0.87 [0.85–0.89]); yet building-contact (0.85 [0.83–0.87]) and room-contact (0.82 [0.80–0.84]) network models also yielded high performance.

We then investigated models with fewer variables, by using only risk factors (ie, variables identified as significant; p<0.05 in table 1) among hospital contextual and ward-contact network variables. Clinical, room-contact network, and building-contact network variables were excluded due to comparably lower performance. Models based only on risk factors have equal performance to models including all variables (table 2; figure 2). Furthermore, the combined
The risk-factor model has the highest positive predictive value (0.87) and positive likelihood ratio (9.67) compared with all other variable-set models (table 2), in addition to high calibration (appendix p 14).

Using a stepwise-variable-elimination approach (appendix p 17), we ranked the combined set of risk factors (ie, hospital contextual plus ward-contact network). The hospital contextual variable “background hospital COVID-19 prevalence” was most predictive, followed by two ward-contact network variables: the infected contact network, which measures the network distance to all infectious cases, and the infected degree and degree centrality, which measures the direct contacts to infectious cases. A parsimonious model based on these three variables alone achieved AUC-ROC of 0.85 (95% CI 0.82–0.88), amounting to 95.5% of the combined model performance (appendix p 17). The same top three variables were also found when applying stepwise variable elimination to the entire variable set and to all the risk factors (table 2).

To validate the predictive power of contact-network variables, we applied our risk-factor models (without recalibrating the hyperparameters) to a Geneva-based geriatric hospital group during their first surge in cases (March 1–May 31, 2020). Over that period, 281 COVID-19 cases (138 COCIs and 143 HOCIs) were reported. Cases peaked on March 26, 2020, with 15 newly identified cases (nine HOCIs and six COCIs), reflecting the height of the early epidemic in Switzerland (figure 3A). In this dataset, ward-level and building-level data were unavailable; hence, we constructed room-contact networks. On the basis of only hospital contextual risk factors, the model achieved a high prediction accuracy, but the inclusion of room-contact risk factors further increased performance (table 2).

For further validation, we used additional data from the same London hospital group collected during an endemic period following surge two in the UK (April 2–Aug 10, 2021). During this time, 1-4 daily cases were reported on average, with no surging behaviour (figure 3B). Compared with UK surges 1 and 2, HOCIs constituted a lower percentage of all cases (186 [12.9%] of 1446 COVID-19 cases were HOCI compared with 167 [15.1%] of 1107 in UK surge one, and 406 [17.8%] of 2276 in UK surge two; appendix p 10). In this endemic setting, we found that the hospital contextual risk-factor model performed poorly with low sensitivity and specificity (table 2). The ward-contact network risk-factor model had substantially improved performance compared with the hospital contextual model. By further

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Table 2: Summary of test and validation set performance across variable groups

<table>
<thead>
<tr>
<th>Variable Set</th>
<th>AUC-ROC (95% CI)</th>
<th>Balanced accuracy</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Positive predictive value</th>
<th>Negative predictive value</th>
<th>Positive likelihood ratio</th>
<th>Negative likelihood ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test set performance models based on variable sets</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All types: patient clinical, hospital contextual, and network-derived</td>
<td>0.89 (0.88–0.90)</td>
<td>0.85</td>
<td>0.85</td>
<td>0.84</td>
<td>0.78</td>
<td>0.41</td>
<td>5.31</td>
<td>0.18</td>
</tr>
<tr>
<td>Patient clinical</td>
<td>0.64 (0.62–0.66)</td>
<td>0.61</td>
<td>0.46</td>
<td>0.75</td>
<td>0.55</td>
<td>0.44</td>
<td>1.84</td>
<td>0.72</td>
</tr>
<tr>
<td>Hospital contextual</td>
<td>0.82 (0.80–0.84)</td>
<td>0.80</td>
<td>0.87</td>
<td>0.73</td>
<td>0.68</td>
<td>0.37</td>
<td>3.22</td>
<td>0.18</td>
</tr>
<tr>
<td>Contact networks (all)</td>
<td>0.88 (0.86–0.90)</td>
<td>0.84</td>
<td>0.85</td>
<td>0.83</td>
<td>0.77</td>
<td>0.40</td>
<td>5.00</td>
<td>0.18</td>
</tr>
<tr>
<td>Room</td>
<td>0.82 (0.80–0.84)</td>
<td>0.80</td>
<td>0.77</td>
<td>0.82</td>
<td>0.74</td>
<td>0.41</td>
<td>4.28</td>
<td>0.28</td>
</tr>
<tr>
<td>Ward</td>
<td>0.87 (0.85–0.89)</td>
<td>0.85</td>
<td>0.90</td>
<td>0.80</td>
<td>0.75</td>
<td>0.39</td>
<td>4.50</td>
<td>0.13</td>
</tr>
<tr>
<td>Building</td>
<td>0.85 (0.83–0.87)</td>
<td>0.84</td>
<td>0.90</td>
<td>0.79</td>
<td>0.74</td>
<td>0.38</td>
<td>4.29</td>
<td>0.13</td>
</tr>
</tbody>
</table>

Test set risk-factor variable models

<table>
<thead>
<tr>
<th>Variable Set</th>
<th>AUC-ROC (95% CI)</th>
<th>Balanced accuracy</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Positive predictive value</th>
<th>Negative predictive value</th>
<th>Positive likelihood ratio</th>
<th>Negative likelihood ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospital contextual risk factors</td>
<td>0.82 (0.80–0.84)</td>
<td>0.80</td>
<td>0.89</td>
<td>0.70</td>
<td>0.66</td>
<td>0.36</td>
<td>2.97</td>
<td>0.16</td>
</tr>
<tr>
<td>Network (ward) risk factors</td>
<td>0.87 (0.85–0.89)</td>
<td>0.85</td>
<td>0.91</td>
<td>0.79</td>
<td>0.86</td>
<td>0.42</td>
<td>9.44</td>
<td>0.16</td>
</tr>
<tr>
<td>Combined (hospital contextual and network [ward]) risk factors</td>
<td>0.89 (0.88–0.90)</td>
<td>0.87</td>
<td>0.91</td>
<td>0.82</td>
<td>0.87</td>
<td>0.42</td>
<td>9.67</td>
<td>0.14</td>
</tr>
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</table>

Validation set performance for models from surge 1 in Geneva hospital (epidemic)*

<table>
<thead>
<tr>
<th>Variable Set</th>
<th>AUC-ROC (95% CI)</th>
<th>Balanced accuracy</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Positive predictive value</th>
<th>Negative predictive value</th>
<th>Positive likelihood ratio</th>
<th>Negative likelihood ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospital contextual risk factors</td>
<td>0.84 (0.82–0.86)</td>
<td>0.82</td>
<td>0.97</td>
<td>0.66</td>
<td>0.68</td>
<td>0.31</td>
<td>2.85</td>
<td>0.05</td>
</tr>
<tr>
<td>Network (room) risk factors</td>
<td>0.80 (0.77–0.83)</td>
<td>0.80</td>
<td>0.76</td>
<td>0.80</td>
<td>0.78</td>
<td>0.39</td>
<td>4.75</td>
<td>0.29</td>
</tr>
<tr>
<td>Hospital contextual and network (room) risk factors</td>
<td>0.88 (0.86–0.90)</td>
<td>0.84</td>
<td>0.97</td>
<td>0.71</td>
<td>0.72</td>
<td>0.32</td>
<td>3.34</td>
<td>0.04</td>
</tr>
</tbody>
</table>

Validation set performance for London hospital group after surge 2 in the UK (endemic)†

<table>
<thead>
<tr>
<th>Variable Set</th>
<th>AUC-ROC (95% CI)</th>
<th>Balanced accuracy</th>
<th>Sensitivity</th>
<th>Specificity</th>
<th>Positive predictive value</th>
<th>Negative predictive value</th>
<th>Positive likelihood ratio</th>
<th>Negative likelihood ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Hospital contextual risk factors</td>
<td>0.49 (0.46–0.52)</td>
<td>0.62</td>
<td>0.56</td>
<td>0.68</td>
<td>0.56</td>
<td>0.38</td>
<td>1.75</td>
<td>0.65</td>
</tr>
<tr>
<td>Network (ward) risk factors</td>
<td>0.63 (0.60–0.66)</td>
<td>0.71</td>
<td>0.66</td>
<td>0.76</td>
<td>0.67</td>
<td>0.39</td>
<td>2.75</td>
<td>0.45</td>
</tr>
<tr>
<td>Hospital contextual and network (ward) risk factors</td>
<td>0.68 (0.64–0.70)</td>
<td>0.74</td>
<td>0.70</td>
<td>0.78</td>
<td>0.70</td>
<td>0.39</td>
<td>3.18</td>
<td>0.38</td>
</tr>
</tbody>
</table>

Performance is measured using AUC-ROC, balanced accuracy, sensitivity, specificity, positive predicted value, negative predicted value, the positive likelihood ratio, and the negative likelihood ratio, which operate on a collapsed confusion matrix to reduce bias (appendix p 7). AUC-ROC=area under the receiver operating characteristic curve. *For this non-UK hospital, contact-network risk factors are derived from the available room-contact network. †Contact-network variables were derived by use of the ward contact network (ie, the most predictive contact definition identified in training and testing).
variable integration, performance was marginally improved with the combined risk-factor model and achieved higher AUC-ROC, sensitivity, and specificity as compared with the previous two models (table 2).

Discussion

We used network analysis in combination with machine learning to predict patient-level HOCI using routinely captured hospital data. To our knowledge, this is the first study to forecast individual patient HOCIs by extracting patient contact networks from bed records. Together with hospital contextual variables, we report patient contact-network centrality as a significant HOCI risk factor, able to increase predictive performance across all datasets analysed.

Transmission of SARS-CoV-2 in health-care settings has been associated with features such as limited isolation capacity, suboptimal individual infection prevention practices, physical distancing, presenteeism, environmental ventilation, and contaminated fomites, which can all be linked to particular patient groups. In our training and testing data, patients managed in elderly care, general medicine, renal, and surgical units were significantly over-represented in the HOCI group (table 1). Staffing levels and stress in critical care; complex pathways and excess movements, resulting in high contacts amongst surgery patients; and the strong community links in renal wards might have exacerbated transmission. Older patients and male gender identity being significantly over-represented in HOCIs reflects known features of the wider pandemic. Although IPC focuses on demographic and individual clinical risk variables, our results show that such fixed variables are least predictive overall. Modern IPC might therefore improve management of outbreaks by including contextual and dynamic risk factors.

Behavioural factors, contact density, and ventilation between locations are known to affect risk of COVID-19 acquisition. These factors are consistent with the hospital contextual risk factors identified in our work. We found that background COVID-19 prevalence within the hospital group was the most predictive variable in our training and test data collected during pandemic surges. Although high case numbers increase transmission sources, background prevalence can also be a proxy for staffing stress and density changes, acting as potential exacerbators. Similarly, high HOCI risk from increased hospital-bed occupancy could be due to high patient loads, increased density, and staffing pressures, which make IPC challenging. Similar to other HCAIs, length of stay was significantly higher for HOCIs (table 1). Length of stay and consecutive length of stay both being significantly longer in HOCIs than in controls also supports genomic analysis suggesting COVID-19 acquisition can be linked to previous admissions. Increased movement rates (ie, bed, room, ward, and site moves) were reported as a risk factor for HCAI locally, yet it was not significantly
different for HOCIs in our data (table 1). The risk from movement rates alone is likely to be too general for HOCI, without specificity, and better captured via measures of contact-network centrality. Altogether, models based on hospital contextual variables showed strong predictive performance across epidemic surges. However, including network variables increased performance most notably in the endemic validation data (table 2).

Most contact-network variables (24 of 30 investigated, eight from each contact definition) were significantly higher in HOCIs (table 1), and the model based only on contact-network variables was as predictive as the model containing all variables (table 2; figure 2). The underlying network structure might, therefore, hold features exploitable for HOCI prediction with network mining tools. HOCIs were significantly more central in contact networks. Few studies have used contact data to investigate HCAI, and most have considered only direct contacts (ie, network degree). Similarly, COVID-19 transmission analysis outside hospital settings has been limited to direct contacts. Consistent with these studies, our results show direct contacts as a strong risk factor of infection. Yet, the infected contact network (ward), measuring network connectedness to all known infections, was more predictive than direct infectious contacts (ie, infected degree), suggesting the presence of longer and indirect transmission chains that can affect contact tracing. Alternatively, disrupting underlying network connectivity by targeting patients with high centralities, together with screening and isolation based on risk factors, could be effective to reduce onward transmission.

To show generalisability, we applied our framework to data gathered from a hospital group that differed in both type (ie, geriatric vs long-term care) and country (ie, Switzerland vs the UK). Despite scarce contact data (ie, only room-level data were available), the framework was still highly predictive, and importantly, performance increased through the inclusion of contact-network risk factors. To further showcase its generalisability, we analysed data from the same London hospital group at a later date under differing epidemiological (ie, endemic) conditions (appendix p 10), changing IPC measures, newly emerging variants, and increasing vaccination rates. Although our framework achieved weaker performance on the endemic validation dataset, the inclusion of patient contact-network risk factors at the ward level substantially increased performance as compared with hospital-contextual risk factors, which did not have predictive capability (table 2).

The emergence of large databases with granular detail has allowed the construction and application of contact networks that can be integrated into routine IPC and public health policy. For instance, recorded movements within hospital (as studied here) or Bluetooth interactions of mobile users (eg, Corona-Warn-App in Germany) provide informative datasets that account for various underlying proxies in human interaction. The ubiquity of such data to construct contact networks is likely only to expand, with select hospitals introducing radio-frequency-identification tracking. Aimed at exploiting these emerging sources of data, our dynamic disease forecasting framework is designed to be portable to a range of settings and variables. The framework offers precise individual predictions of risk of infection acquisition and is thus amenable for risk stratification in real-time, which can serve to guide dynamic IPC resource allocation for rapid screening, isolation, and grouping of patients at high risk of infection acquisition. By incorporating complex multimodal data sources into a single measure of predicted risk, our framework produces relevant and actionable outputs preventing disease acquisition.

Major challenges to effective IPC activity are low bed capacity and inadequate and overwhelmed isolation capacity, in addition to insufficient staffing and microbiological testing resources. These challenges to IPC were vastly exacerbated by the COVID-19 pandemic. We envisage the proposed framework to be used within a modern, data-driven IPC patient management system and able to assist optimal decisions in real-world scenarios. The predicted risk score for each patient can be used by clinicians to rank and prioritise (eg, identify patients at high risk for infection for isolation or grouping followed by targeted enhanced testing). In this way, HOCIs could be identified at the earliest opportunity, which in turn could optimise IPC measures and treatment. Patients at low risk of infection acquisition could also be potentially moved back to regular patient management faster, saving resources that are in demand. However, further work is needed to evaluate the direct implications (ie, clinical and economic) of identifying patients at high risk of infection. In addition to actionable clinical points, a key aspect of this framework is its dynamism and its ability to generate insight on demand. By aggregating complex data sources into single interpretable risk scores, a range of risk sources and their interactions are made accessible to hospital teams. Such data-driven insights, always integrated within human decision making, can enable hospital teams to become more flexible and responsive to complex, rapidly emerging disease threats.

Our study has several limitations. First, our contact definitions might not fully capture transmission (eg, connections via health-care workers), indirect transmission over surfaces; non-room, ward, or building contact; or interactions from visitors. However, routinely collected patient bed allocations have been shown to capture implicitly non-patient interactions that align with organisational and speciality hospital structures. Staff and visitor contact data were not available in our data due to privacy restrictions, but such data should be investigated, in accordance with privacy prescriptions. Second, since our training and testing period occurred largely
before the UK’s vaccination rollout, we were unable to include vaccination status as a patient variable. With increasing levels of natural and induced immunity, inclusion of vaccination and recovery status might improve predictions; emerging new variants and incomplete vaccine coverage make the levels of susceptibility uncertain. Third, patient ethnicity was not available in our study. Due to its contextual complexities, and being a previously identified risk factor, ethnicity warrants specific and increased investigation in the future. Fourth, our data did not include ventilation or specific information about room arrangements (appendix p 2), which contribute to COVID-19 transmission. However, without accounting for ventilation, our models were highly predictive. Finally, various aspects of hospital organisation were altered across the pandemic, including changes in screening practice, personal protective equipment, or bed placement, which were not encoded here as variables.

Overall, our study emphasises that dynamic networks of patient contacts can aid personalised predictions of infection. Our study applies to respiratory virus transmission in hospital, using widely available patient bed records. Further work is needed to extend this framework to other infectious diseases, assessing the types of contact required for transmission, evaluating the implications of identifying a patient at high risk of infection acquisition, and understanding how it could be integrated into IPC more generally.

Contributors
AM, JRP, RLP, SM, and MB contributed to study concept and design. JRP, MA, SM, NZ, and FR contributed to data acquisition. AM, JRP, MA, and AH contributed to the initial manuscript drafting. All authors contributed to data interpretation and final revisions of the manuscript. AH and MB contributed to study supervision. AM, JRP, RLP, MA, SM, SH, AH, and MB contributed to the discussion of the results and reviewed the data. All authors had full access to all the data in the study and had final responsibility for the decision to submit for publication.

Declaration of interests
After the analysis in this paper was completed, AM and MB received funding from UKRI Research England via the MedTech SuperConnector (awarded on June 1, 2022) for commercial viability testing of infection prevention models. All other authors declare no competing interests.

Data sharing
The processed anonymised training and testing dataset used in this study can be available on reasonable request to the corresponding authors. Patient pathways will not be provided as these are withheld by the corresponding authors’ organisation to preserve patient privacy. Data from the Imperial Clinical Analytics Research and Evaluation platform used in this study can be available to researchers on request. External validation data sources will not be provided as these are withheld by owners. Data regarding hospital COVID-19 admissions are freely available via the NHS COVID-19 hospital activity webpage (https://www.england.nhs.uk/statistics/statistical-work-areas/covid-19-hospital-activity). The code of the method is freely available as an R package (https://github.com/barahona-research-group/Dynamic-contact-infection-forecast) with sample data sets.

Acknowledgments
We thank Imperial College London’s NHS Infection Prevention and Control team and the iCARE team for supporting data access, cleaning, and interpretation. AM was supported in part by a scholarship from the Medical Research Foundation National PhD Training Programme in Antimicrobial Resistance Research (MRF-14/5-0004-TPG-AVIS0) and by the NIHR Academy. RLP was funded by the Deutsche Forschungsgemeinschaft (Project-ID 42678381-TRR 295). MA and SH received funding from the Swiss National Science Foundation. AH is an NIHR Research Senior Investigator. AH is partly funded by the NIHR Health Protection Research Unit in Healthcare Associated Infections and Antimicrobial Infections in partnership with Public Health England, in collaboration with Imperial Healthcare Partners, University of Cambridge, and University of Warwick (NIHR grant code: NIHR200876). NZ was funded by the NIHR Health Protection Research Unit. AM, RLP, and MB acknowledge funding from the Engineering and Physical Sciences Research Council (grant EP/N014529/1) to MB, supporting the Engineering and Physical Sciences Research Council Centre for Mathematics of Precision Healthcare. AH and MB also received financial support from WHO for the investigation. The research was also supported by the NIHR Imperial Biomedical Research Centre and by the iCARE environment, and used the iCARE team and data resources. The views expressed in this publication are those of the authors and not necessarily those of the NHS, the NIHR, the Department of Health and Social Care, Public Health England, or WHO.

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