ORIGINAL ARTICLE

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Three-Dimensional Disease Outbreak Surveillance System in a Tertiary Hospital in Singapore: A Proof of Concept

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Abstract

Objective: To develop an electronic surveillance system that provides prompt in-depth situational infectious disease risk and linkage analysis for inpatients in a tertiary hospital.

Patients and Methods: All patients admitted to Singapore General Hospital (SGH), a 1900-bedded tertiary care hospital, are included in routine surveillance. The 3-Dimensional Disease Outbreak Surveillance System (3D-DOSS) was developed to spatiotemporally represent inpatient surveillance data on a "digital twin" of SGH and evaluated for performance in surveillance, contact tracing, and outbreak investigations. This study was conducted over a 12 month period (October 1, 2020 to September 30, 2021).

Results: The 3D-DOSS surveillance module identified an influenza cluster of 10 inpatients in November 2018, mapping retrospective data between September 2018 and December 2018. Seventy-six clusters of 2 or more linked patients with health care–associated *Klebsiella pneumoniae* carbapenemase–type carbapenemase-producing *Enterobacteriaceae* were detected in SGH in 2 years (2018 and 2019). The 3D-DOSS contact tracing module promptly identified 44 primary and 162 secondary inpatient contacts, after exposure to a health care worker with coronavirus disease 2019 in April 2021. For outbreak mapping, 24 patients with OXA-48 were mapped on October 22, 2020, using 3D-DOSS to determine their spatiotemporal distribution.

Conclusion: The integration of health care data and representation on a virtual hospital digital twin is a useful tool in an outbreak alert and response framework. Infectious disease surveillance systems, which are syndrome-based, that can access real-time data, and can incorporate movement networks, can potentially enhance health care–associated infection prevention and preparedness for disease X.

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The coronavirus disease 2019 (COVID-19) pandemic has exposed vulnerabilities in the hospital system with significant limitations in detection and prevention of health care–associated infection (HAI) clusters.[1] Digital technologies have been leveraged to enhance contact tracing in community settings. However, within complex hospital environments, where patient and staff movement and interpersonal interactions are central to care delivery, tools for contact tracing and cluster detection remain underdeveloped.

Health care–associated infections have significant effect on both finance and health outcomes. In Singapore, the HAIs occur in approximately 11% of hospital inpatients, estimated at 85,000 patients in 2019.[2] A single HAI is associated with 2 additional days in hospital, with an added cost of US $1300.[2] In a Singapore study, health care–associated methicillin-resistant *Staphylococcus aureus* infections were associated with longer hospitalization (32 days vs 7 days) and higher cost (US $18,000 vs US $4500).[3] Unspecified sepsis and pneumonia were the most common HAIs in Singapore in a point prevalence survey.[4] Other HAIs such as central line–associated bloodstream infections are associated with significant mortality, 25% in

Singapore General Hospital (SGH), based on a 3-year cohort, 2018-2020 (unpublished), comparable with other reports.[5-7] Individual patient risk assignment for HAIs is currently not feasible owing to limitations in health care data integration, analyses, and representation.

In a 1-week period between April 27, 2021, and May 5, 2021, a cluster of 40 patients with COVID-19 were identified within 1 ward in Tan Tock Seng Hospital in Singapore. The emergence of the severe acute respiratory coronavirus virus 2 Delta variant (B.1.617.2) with its greater transmissibility and shorter incubation period (than those of the preceding α variant) led to the pandemic breaking through multiple lines of defense such as universal masking and high vaccination coverage.[8] There are no robust electronic surveillance systems for early identification of such geographical clusters in health care settings in Singapore.

The current hospital-based infectious disease surveillance systems lack capacity for granular geographic and patient-level risk data and have an intrinsic lag time, critically limiting their applicability within an outbreak alert and response framework. Building on experience from developing disease surveillance system in a COVID-19 community care facility,[9] we aimed to develop an electronic surveillance system that provides prompt in-depth situational infectious disease risk and linkage analysis for inpatients in a tertiary hospital. Through early identification of at-risk patient contacts and infectious disease clusters, HAIs can potentially be prevented and controlled.

PATIENTS AND METHODS

Setting

Singapore General Hospital is the largest tertiary care multispecialty academic medical center in the SingHealth cluster in Singapore with active hematologic and solid organ transplant services and incorporates a cardiothoracic and national burns center within its premises. It has 1900 beds and more than 80,000 annual admissions. The 29 inpatient wards with single and multibedded rooms are located across 6 floors in 4 blocks of a 7-block building complex. The emergency department, outpatient clinics, pharmacy, and other services occupy the other 3 blocks. The specialized isolation ward has 43 negative and positive pressure single rooms with anterooms prioritized for patients with airborne transmissible infections. The general wards consist of single and multibedded rooms with 4-7 beds in each room and intensive care units with single and double occupancy rooms. Ventilation in nonisolation wards comprises of recirculated air handling systems. The toilet facilities are shared in the multibedded rooms.

The Department of Infection Prevention and Epidemiology is a 41-member team comprising infection prevention nurses, epidemiologists, data system experts, contact tracers, physicians (microbiology, infectious diseases, and occupational medicine), and administrative staff. The epidemiology section develops and maintains infectious disease data systems, sets thresholds and alerts based on surveillance reports, and supports exposure and outbreak management. The infection prevention section develops and implements hospital-wide infection prevention policies and responds to alerts (surveillance and clinical) and outbreaks.

The 3-Dimensional Disease Outbreak Surveillance System Application Framework

The 3-Dimensional Disease Outbreak Surveillance System (3D-DOSS) was developed for use by the epidemiology section of the department, to present routine surveillance data in a format that is time cognizant, enables cluster detection through spatiotemporal visualization, improves efficiency of contact tracing and outbreak mapping, and facilitates prediction analytics. This would inform the team of situational infectious disease risk and move surveillance from a reporting platform to an alert system within an alert-response framework.

As a proof-of-concept project, 3D-DOSS was a stand-alone system that was not integrated into the existing hospital data systems. Data extraction and input was manual and performed for selected scenarios from a 4-year period between 2018 and 2021, to assess applicability and performance. It was not implemented for routine use.

Health Care Data Systems in SGH

Electronic health records have been available in SGH since 2017. Inpatient and outpatient clinical records, medication orders, and laboratory reports are on All Scripts Sunrise Clinical Manager (SCM); radiological reports and images are on Radiological Information Systems and Picture Archiving and Communications Systems; and inpatient movement information is on SAP, a patient tracking system.

The Integrated Health Information System (IHiS), formed in 2008, provides an integrated IT infrastructure for public health care institutions in Singapore. The SingHealth-IHiS Electronic Health Intelligence System (eHIntS) is SingHealth's Enterprise Analytic Platform, which uses Oracle databases to store information from SCM, Radiological Information Systems and Picture Archiving and Communications Systems, and SAP. These can be accessed and used for analytics and reporting. After customization by IHiS, surveillance databases are developed and maintained in eHIntS by the epidemiology team.

Digital Twin and Spatiotemporal Data Mapping

The mapping prototype for 3D-DOSS was developed to spatiotemporally represent SGH inpatients within a digital twin built on the Unity gaming platform (Unity technologies) (Figure 1A). Unity is a cross-platform 3D game engine that runs using certain programming languages such as C# and C++. It can create digital environments that replicate real-world dimensions. The gaming engine allows for first person and global views. Patient interactions in space and time can be observed when patient movement data are integrated (Figure 1B).

AutoCAD formatted (proprietary information) floor maps last updated on April 2021 were used as a base template. The bed layout and numbering and plumbing network data provided by the Bed Management Unit and the facilities department, respectively, were used to build the digital replica—through indexing of all objects on the map. A secondary map of trackable items was used as a link between the clinical and map data sets. Inpatient ward locations have Real-time Locating System (RTLS) for patient tracking, but this was not incorporated into the prototype as the existing RTLS system was not designed to provide accurate triangulation, with tracking limited to rooms but not beds. Hence, bed allocation data from SAP patient management system was integrated into 3D-DOSS for spatial inference.

Data Manipulation and Processing

Data downloaded from the various sources were manipulated within the Oracle 12c database before exporting the flat files to a digital twin environment (JetBrains PyCharm version 2020.2.5; AxoMem xBase 0.9; AxoMem xScape 0.9; Unity 2020 LTS). The environment contained 3 main components; the first was a read of the base maps and setting up of the digital space. The second required a script to load patient variables and give the overall picture reflected on the base map. The final component was the visual slicer and slider to indicate the variable of interest—only 1 slicer (binary output) was incorporated in the base model, to enable interaction between the datasets. Data were further differentiated to include temporal differences from the last observed data point (Supplementary Figure 1).

Surveillance, Contact Tracing and Outbreak Mapping Modules

Routine infectious disease surveillance performed by the department is limited to inpatients and is predominantly pathogen-based targeting—selected multidrug-resistant organisms, respiratory viruses, gastrointestinal pathogens, vaccine-preventable infections, mycobacteria, and fungi.

Acute respiratory illness (ARI) syndrome—based staff surveillance[10] was developed and used early in the COVID-19 pandemic phase when staff reporting requirements were heightened and was discontinued when staff reporting reverted to prepandemic state. Determination of staff-staff and staff-patient contact networks is limited by the absence of electronic staff movement tracking in SGH. Acute respiratory illness syndrome—based inpatient surveillance was developed during the COVID-19 pandemic.

Surveillance, contact tracing, and outbreak databases are developed within eHIntS and

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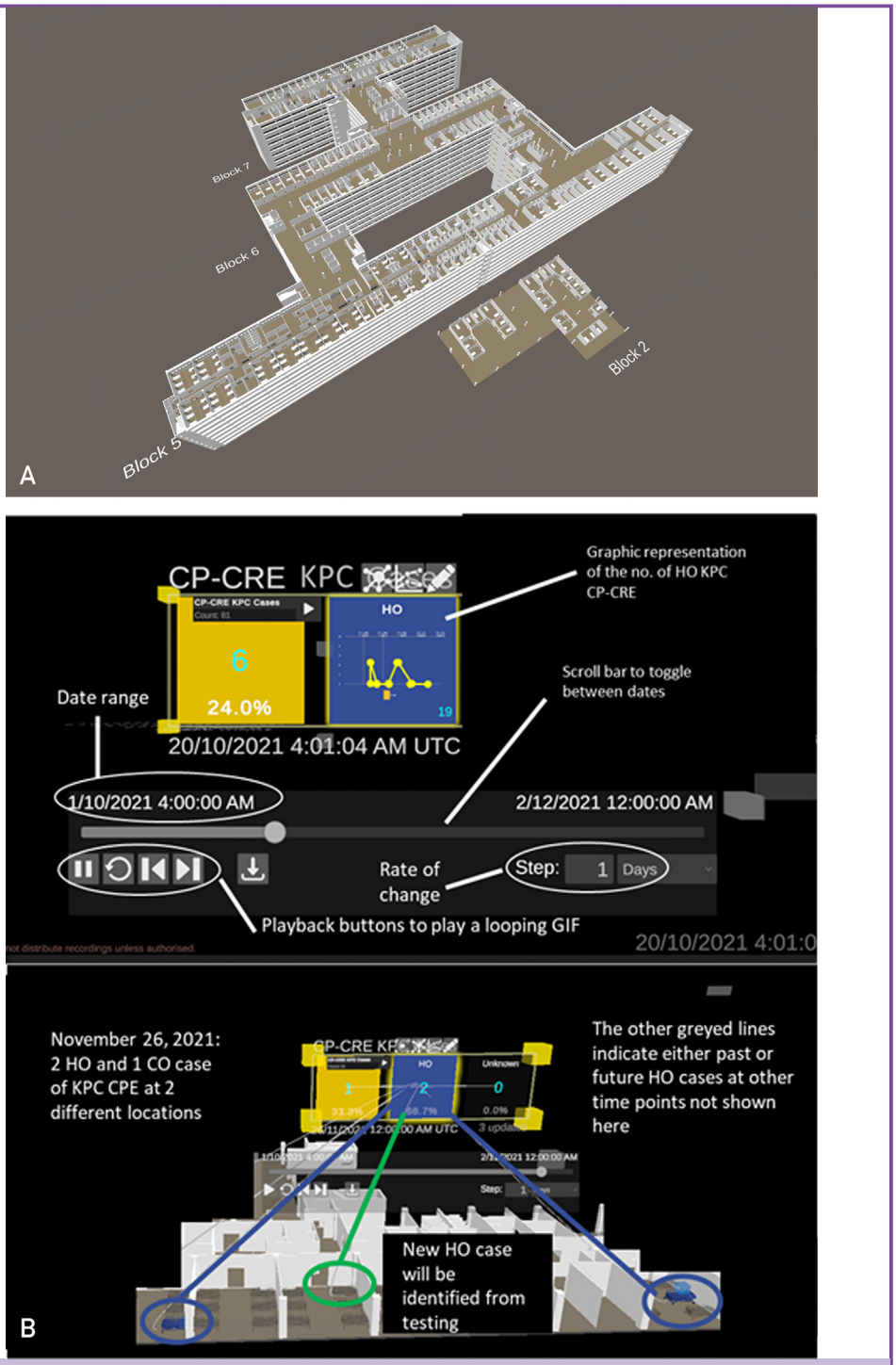

FIGURE 1. Three-dimensional representation of clinical hospital blocks (A). Multilevel data integration and representation on the 3-Dimensional Disease Outbreak Surveillance System (3D-DOSS) (B). CO, community onset, defined as a positive sample taken less than 72 hours after admission; CP-CRE, carbapenemase-producing carbapenem-resistant *Enterobacteriaceae*; CPE, carbapenemase-producing *Enterobacteriaceae*; HO, health care onset, defined as a positive sample taken more than 72 hours after admission. KPC, *Klebsiella pneumoniae* carbapenemase.

supplemented by patient movement data from the SAP patient management system. These were integrated into the 3D-DOSS mapping prototype to assess their performance in disease and syndromic surveillance, cluster detection, contact tracing, and outbreak investigations.

In the surveillance module, 3 separate components were assessed in 3D-DOSS: (1) laboratory-based influenza-specific ARI surveillance, (2) syndromic ARI surveillance, and (3) *Klebsiella pneumoniae* carbapenemase (KPC)—type carbapenemase-producing *Enterobacteriaceae* (CPE) surveillance.

Influenza-specific ARI surveillance was based on laboratory data (Seegene Anyplex II RV16 Detection Multiplex polymerase chain reaction kit)[11] for influenza collected between September 2018 and December 2018. Health care—onset (HO) influenza is defined as influenza diagnosed on respiratory sample taken 3 days (incubation period) after hospital admission. Cases are considered linked when they have been in the same cohort room within 7 days (infectious period) of the index patient's influenza test with positive results.

Syndromic ARI surveillance system developed during the COVID-19 pandemic in 2020 identifies inpatients with any 1 of the following 5 respiratory symptoms: sore throat, cough, rhinorrhea, loss of taste and smell, and dyspnea, as documented by the nursing team daily in the SCM flowsheet and accessed using the eHIntS. Definitions for HO and linkage were similar to those for influenza. Data were incorporated into the 3D-DOSS for prospective ARI cluster detection over a 6-month period between June 2020 and December 2020.

Multidrug-resistant organism control program in SGH includes an active surveillance program for CPE. Selected high risk-patient cohorts such as patients with a prolonged hospital stay of greater than 2 weeks undergo rectal swabs or stool sampling for molecular testing for the presence of carbapenemase genes. Contact tracing and CPE screening is performed for patients who had shared the same room as the CPE patient in the preceding 14 days or from the time of admission to the identification of a sample with positive results, whichever was later. Patients with HO KPC CPE detected on routine surveillance or from clinical specimens (colonization and/or infection) in the 2 years preceding COVID-19 pandemic (2018 and 2019) were represented on the 3D-DOSS to visualize geographical distribution and clustering, with HO defined as a positive sample taken 3 days after hospital admission. Patients with community-onset KPC CPE are defined as those with samples showing positive results taken within 72 hours of admission. Any 2 or more patients with KPC CPE who shared the same room in the 2 weeks preceding CPE sampling were considered linked.

Routine surveillance for CPE involves trending of CPE types in each ward and when there is an increase in the mean number of patients with a specific CPE type in a ward over a 1-month period, they are reviewed for spatiotemporal linkage (shared room within preceding 2 weeks). Then, screening samples for CPE culture are taken from the epidemiologically linked patients. Those with common CPE type and bacterial species are considered linked and further outbreak investigations may include whole genome sequencing.

In the contact tracing module, 3D-DOSS was used for contact tracing for a single COVID-19 exposure event in April 2021, in the inpatient wards. At-risk contacts were defined as persons within 2 m from the index patient if the index patient was a health care worker (HCW) or within the same room as the index patient if the index patient was an inpatient, with a temporal overlap of at least 15 minutes. The infectious period was 7 days before laboratory confirmation for asymptomatic persons and 48 hours before symptom onset for symptomatic persons with the end of the infectious period being 7 days from the date of a positive-result test (asymptomatic) or symptom onset (symptomatic) or transfer to isolation room, whichever was earlier.[12] Secondary contacts were contacts of primary contacts, identified based on the similar spatiotemporal criteria. For the single exposure event that was assessed, the index was a HCW and patient list for mapping that was obtained from the daily ward round list and through the HCW interview to determine proximity.

In the outbreak mapping module, HO OXA-48 type CPE (defined as OXA-48 CPE isolates from surveillance or clinical samples collected more than 72 hours after hospital

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TABLE 1. KPC CPE in SGH in 2018 and 2019

	Outbreak KPC carriage				Nonoutbreak KPC carriage
Outbreak period	Patients	Number of clusters	Patients per cluster	Bacterial isolates	Patients
May 2018	32	4	2-4	*Klebsiella pneumoniae*, 4 *Klebsiella aerogenes*, 1 *Klebsiella sp*, 1 *Escherichia coli*, 2 *Enterobacter cloacae*, 7	39 (1 ICU)
November 2018	46	15	2-12	*Klebsiella pneumoniae*, 6 *Klebsiella aerogenes*, 2 *Klebsiella sp*, 4 *Escherichia coli*, 7 *Enterobacter cloacae*, 8 *Serratia marcescens*, 1	55 (9 ICU)
October 2019	25	8	2-6	*Klebsiella pneumoniae*, 6 *Klebsiella sp*, 2 *Escherichia coli*, 1 *Enterobacter cloacae*, 2 *Citrobacter koseri*, 1	57 (3 ICU)

CPE, carbapenemase-producing *Enterobacteriaceae*; ICU, intensive care unit; KPC, *Klebsiella pneumoniae* carbapenemase; SGH, Singapore General Hospital.

admission) increased from a mean of 2 patients per month to 13 in the first 2 weeks of October 2020, triggering an outbreak investigation.[13] This outbreak data from October 22, 2020 was mapped onto the 3D-DOSS.

Results from the 3D-DOSS were compared with those of routine surveillance, contact tracing, and outbreak mapping. For influenza and KPC surveillance, data from the pre−COVID-19 pandemic period were used because there were no HO influenza after the onset of COVID-19 pandemic and the KPC surveillance was interrupted in the first 2 years of COVID-19 pandemic.

Ethics

This study was reviewed by the SingHealth Centralised Institutional Review Board and determined not to require further ethical deliberation because it involves development of customized geospatial mapping for disease surveillance and outbreak management (Centralised Institutional Review Board Ref: 2021/2188).

RESULTS

The inpatient wards underwent significant modifications during the COVID-19 pandemic. With each pandemic surge, selected general wards were converted into COVID-19 isolation wards or acute respiratory surveillance wards for confirmed and suspected patients, respectively, as part of a hospital-wide infection prevention effort.[14] Digital twin was based on the original ward layout. In the 2 years before the pandemic (2018 and 2019), the monthly average number of inpatient beds was 1730, patient admissions were 6798, and length of stay was 6 days. The corresponding figures in the 2 years during the COVID-19 pandemic (2020 and 2021) were 1893 inpatient beds per year, 6130 admissions per year, and 6.9 average length of stay per year, respectively. The average number of inpatient bed/ward movements per patient was 5 (SD=2.3).

In the surveillance module,−first, influenza-specific ARI surveillance between September 2018 and December 2018 identified 1 influenza cluster of 10 inpatients in November 2018. This had not previously been detected. Second, syndromic ARI surveillance between June 2020 and December 2020 did not identify any infection-related ARI clusters in non−COVID-19 inpatient locations. This was attributed to enhanced infection

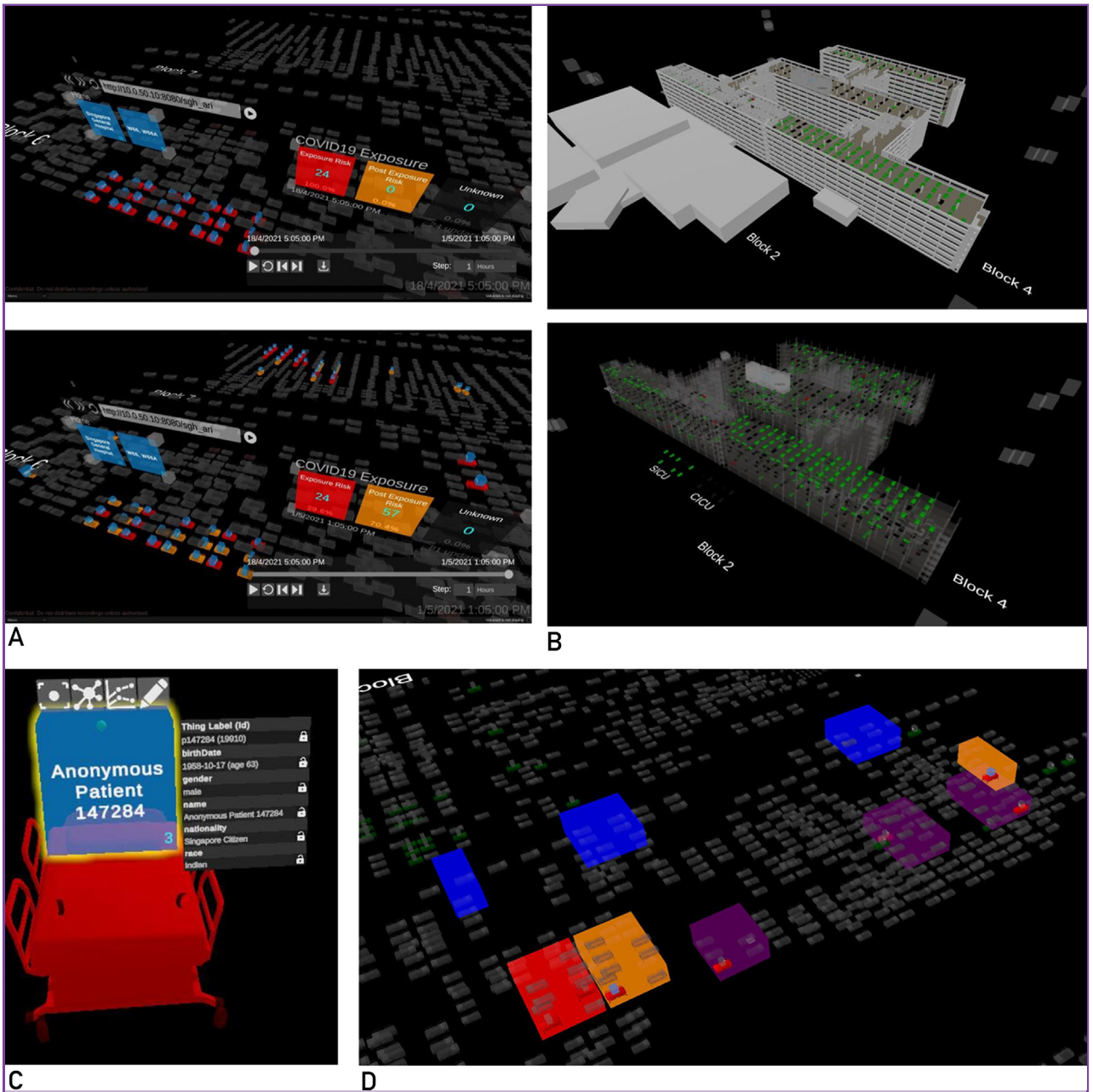

FIGURE 2. Inpatient contact tracing for health care workers with coronavirus disease (COVID-19) on April 18, 2021. Exposure risk: primary contacts (in red), 24. Post exposure risk: secondary contacts (in orange), 57. Data represented at 2 time points illustrating primary contacts and subsequent secondary contacts due to inpatient transfers (A). OXA-48 hospital-wide outbreak point prevalence on October 22, 2020. Patients confirmed with OXA-48 carbapenemase-producing *Enterobacteriaceae* (CPE) are indicated in red. Green-colored beds indicate patients who were negative for OXA-48 CPE, and purple-colored beds indicate patients who subsequently showed positive results for OXA-48 CPE during the admission. Two views represented, exterior and interior with better visualization of inpatient locations (B). Bed and patient data represented on the digital twin (C). Inpatient rooms can be represented by colored boxes set to different cluster thresholds (D). Orange: 1 patient in a multibedded room with CPE; purple: 1 patient in a multibedded room with CPE with at-risk contact patient(s) who eventually test positive for same CPE; red: 2 or more patients in a multibedded room with same CPE; blue: 1 or more at-risk patients who have had contact with patient(s) with CPE.

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TABLE 2. Performance of 3D-DOSS in Comparison With Routine Methods for Surveillance, Contact Tracing, and Outbreak Mapping

Modules	Indicator	Routine	3D-DOSS	Remarks
Surveillance	ARI: influenza	Aggregate numbers trended with location-based clustering determined manually	Cases mapped onto digital twin with representation of spatiotemporal linkage	Eliminated need for manual spatiotemporal linkage
	ARI: syndrome	Charts for individual wards reviewed with location-based clustering determined manually	Cases mapped onto digital twin with representation of spatiotemporal linkage	Eliminates need for a review of charts for individual wards. Eliminates need for a manual spatiotemporal linkage. Enables incorporation of environmental and patient variables for an in-depth transmission risk analysis
	KPC CPE	Aggregate numbers trended with location-based clustering determined manually	Cases mapped onto digital twin with representation of spatiotemporal linkage	Eliminates need for a manual spatiotemporal linkage. Enables incorporation of microbiological, molecular, and patient variables to allow for complexity of CPE linkage analysis. Enables in-depth transmission risk analysis
Contact tracing	COVID-19	Manual data extraction and matching and extraction from various hospital systems	Contacts (primary and secondary) immediately identified on digital twin	Enables prompt identification of at-risk contacts. Discharged contacts not identified by 3D-DOSS
Outbreak mapping	OXA-48 CPE	Manual data extraction and matching from various hospital systems followed by mapping on 2D floor maps	Cases represented on digital twin	Enables determination of location specific clustering and linkage. Enables incorporation of microbiological, molecular, and patient variables to allow for complexity of CPE outbreak investigation

3D-DOSS, 3-Dimensional Disease Outbreak Surveillance System; ARI, acute respiratory illness; COVID-19, coronavirus disease 2019; CPE, carbapenemase-producing *Enterobacteriaceae*; KPC, *Klebsiella pneumoniae* carbapenemase.

prevention measures both in the community and within health care.[15] Noninfective ARI symptom–based clustering (determined through a case review) was observed among oncology patients with pulmonary malignancies. Finally, the 3D-DOSS identified 76 clusters of 2 or more linked patients with HO KPC CPE, between 2018 and 2019, corresponding to 3 outbreaks in non-ICU general wards (May 2018, November 2018, and October 2019) (Table 1). All were identified from screening samples. Of these, 27 clusters had been identified and investigated as true clusters, based on the clustering of bacterial species carrying the KPC gene. In routine infection prevention practice, trigger for epidemiologic linkage evaluation is an increase from the baseline numbers of cases for any given ward over a 1-month period, whereas 3D-DOSS enables prompt determination of epidemiological linkage with the ability to set varying thresholds and parameters. The additional 49 linked KPC CPE clusters may be indicative of cross-species associations through plasmids and other unknown transmission routes.

For the contact tracing module, in April 2021, a doctor was diagnosed with COVID-19 on surveillance polymerase chain reaction testing. Contact tracing using the 3D-DOSS identified 44 primary and 162 secondary inpatient contacts (Figure 2A). Routine contact

TABLE 3. Automated and Semiautomated Infectious Disease Surveillance Systems in Hospitals

Surveillance system	Country	Type of system	HAI targets	Data sources	Data type	Sensitivity	Status of system
HAI-Proactive[19]	Sweden	Fully automated rule-based algorithm	Hospital-onset sepsis, UTI	Structured/ unstructured EHR data	Microbiology, antibiotics, clinical	>85% compared with manual surveillance	Reporting using manual method to health care providers
University Medical Centre Utrecht automated system for SSI[19]	The Netherlands	Semiautomated classification tree	Deep incisional SSI (after TKA, cardiac, spinal, IO surgeries)	Structured EHR data	Administrative, microbiology, antibiotics	>95% compared with manual surveillance	Reporting using online dashboard within institution
Hospital-Associated Infections Database (HAIBA)[19]	Denmark	Fully automated rule-based algorithm	HOB, UTI, CDI, deep incisional SSI (after THA, TKA)	Structured data from national registries	Administrative, microbiology	36% compared with PPS	Reporting using automated output reports
Algorithm development[23]	The Netherlands	Semiautomatic surveillance system	Deep surgical site infections after colorectal surgery	Structured/ unstructured EHR data	Administrative, clinical	98.5%	Algorithm development
Algorithm validation[21]	The Netherlands	Semiautomatic surveillance system	Deep surgical site infections after primary THA or TKA	Structured EHR data	Administrative, clinical, microbiology	93.6%-100%	Validation of algorithm for surveillance system
AODS[18]	Germany	Automated	Pathogen-based clusters	Structured EHR data	Administrative, microbiology	83%-100% detection rate for outbreaks with sporadic pathogens. 33%-100% for outbreaks with endemic pathogens	Assessment of newly developed AODS
HOCI surveillance system[16]	United Kingdom	Automated surveillance system	COVID-19	Structured EHR	Administrative, clinical	Not applicable	Reporting HOCI rates, trends and geotemporal linkage using real-time shifting denominator data and network analysis

AODS, Automated Outbreak Detection Systems; CDI, *Clostridium difficile* infection; COVID-19, coronavirus disease 2019; EHR, electronic health records; HAI, health care–associated infection; HOB, hospital-onset bloodstream infection; HOCI, hospital-onset COVID-19 infection; IO, intraocular; PPS, point prevalence survey; SSI, surgical site infection; THA, total hip arthroplasty; TKA, total knee arthroplasty; UTI, urinary tract infection.

tracing identified 54 inpatient contacts, including an additional 10 who had been discharged. The 3D-DOSS only identifies patients who are still inpatient at any given time point. Secondary contacts are not routinely identified for COVID-19 contact tracing (Supplementary Figure 2). Time taken to collate these data using the traditional method was 3.5 hours compared with 0.5 hours using 3D-DOSS.

In the outbreak mapping module, during the 2020 OXA-48 outbreak, mapping 24 patients with OXA-48 CPE on a single day, October 22, 2020, demonstrated distribution throughout the hospital. With this system, using variations in color, we were able to visualize at-risk patients before they subsequently showed positive results (Figure 2B-D).[13]

Performance of 3D-DOSS compared with the routine processes is given in Table 2.

DISCUSSION

Automated and semiautomated HAI surveillance systems currently in use are largely built for incidence reporting rather than as early alert systems for emerging and re-emerging HAIs[16-23] (Table 3). They are predominantly pathogen or disease specific, are built on data systems with an intrinsic lag time and with exception of intensive care units, and have limited location specific monitoring. They have limited capacity for early detection of clusters of patients with transmissible infections, particularly when confined to specific hospital locations.

Developments in health care information technology have made it possible for surveillance systems that incorporate multiple administrative and clinical data sources into algorithms with increased reliability. Machine learning methods and natural language processing of unstructured data are some techniques that have widened the scope of such systems.[24,25] These capabilities can potentially be applied further upstream from audits and incidence reporting to predictive modeling.[26]

The 3D-DOSS has demonstrated feasibility of health care data integration to spatially represent infectious disease cases and enhance cluster detection capabilities. Cluster detection is currently heavily reliant on clinical observation and recognition. Once clusters are identified, an analysis requires manual data extraction, collation, and organization adding to further delays. Spatial relationships, distances, and patient movement networks are impossible to analyze algorithmically because no digital spatial version of the hospital exists.

In complex health care systems, patients move frequently through hospital locations rapidly escalating cross-infection risk. There is a lack of oversight and understanding of high frequency patient movement networks and nodal contact points within hospitals. Multiple transmission cycles and hospital-wide dissemination are likely to have occurred by the time syndromes are recognized and microbiological diagnoses are made. The effect of intrahospital patient movement on carriage of multidrug-resistant organisms has been evaluated in modeling studies.[27,28] Network analyses can be further developed on data from systems such as the 3D-DOSS.

Through early identification of at-risk contacts and detection of infectious disease clusters, the 3D-DOSS can facilitate interventions to prevent onward disease transmission. The system can support the utilization of mathematical modeling to assign risk to exposed individuals based on distance coordinates, room type, ventilation parameters, drainage system, and transmission modes of disease. Simulations of novel disease outbreaks can enhance preparedness planning to build a more resilient health care system.

Infection prevention programs have generally been broad-based and not targeted at individual patient risks.[29] Transition to electronic health care data and advancements in technology now enable advanced analytics such as machine learning and predictive modeling of HAIs.[30,31] Infection prevention interventions informed by unique individual and environmental risks would be aligned with the delivery of precision medicine in health care.

Limitations of the 3D-DOSS such as lack of access to real-time data and RTLS where movement networks can be determined with greater accuracy. The ability for surveillance algorithms to detect clusters may have also been affected by COVID-19 pandemic-related workflow changes.

The 3D-DOSS was also not integrated into an alert and response framework for early intervention. Developed as a proof-of-concept project, the 3D-DOSS is a stand-alone, time and resource intensive system

requiring manual data extraction and input. For it to be integrated into routine surveillance, the data input has to be real-time or near real-time and data flow has to be automated. In its existing form, the 3D-DOSS is able to capture inpatients only, but not discharged patients. Thresholds for different diseases and syndromes need to be established based on longitudinal data trends. In the syndromic ARI surveillance module, clustering based on symptoms alone identified noninfective clusters. Additional parameters such as C-reactive protein and procalcitonin can be incorporated to improve performance and reduce the number of false-negative clusters. The 3D-DOSS was developed as a system to optimize existing surveillance data, by enabling spatiotemporal visualization and understanding infectious disease burden and risk. It has potential for application of more complex CPE surveillance algorithms.

Hosting and managing the system requires both advanced technological tools and expertise within health care institutions, to develop, integrate, interpret, maintain, and update in response to changes in data systems and clinical and operational workflows. Because each institution has its own ecology and processes, it is not generalizable across different hospitals.

We have demonstrated that the 3D-DOSS system can identify close contacts and clusters of infectious diseases, validating its use in contact tracing, surveillance, and outbreak investigations. It can be configured for various infectious diseases including disease X,[32,33] which represents an unknown pathogen with pandemic potential and hence increase health care preparedness, resilience, and safety.

CONCLUSION

Integration of health care data and representation on a virtual hospital digital twin is a useful tool in an outbreak alert and response surveillance system. Infectious disease surveillance systems that are based on disease syndromes, access real-time data, and incorporate patient (and staff) movement networks can potentially better inform HAI prevention and increase preparedness for disease X.

POTENTIAL COMPETING INTERESTS

Authors Venkatachalam, Conceicao, Lim, and Cheong report receipt of NUC device to run data provided by AxoMem for the period of study. Authors Venkatachalam, Conceicao, Lim, Cheong, Sim, Whiteley, Chow, and Arora report application to SingHealth Research office via the Invention Disclosure Form to allow evaluation for potential intellectual property protection and commercialization. Author Whiteley is the director of AxoMem, the organization receiving payment from the institution for provision of software and technical expertise for the (1) development of the digital twin (3D-mapping replica of the hospital) and (2) integration of patient data onto a commercial platform. Digital twin was built by the epidemiology team under guidance by AxoMem. Algorithms for contact tracing, surveillance and outbreak mapping were developed by the epidemiology team who also independently assessed its (3D-DOSS) performance. Dr Fang reports consulting fees from NTTData for preparing a commercial project proposal (on data cataloguing), not related to this manuscript, and payment or honoraria from the National University of Singapore for teaching a module to undergraduate students on application of data science in health care. All other authors report no conflicts of interest relevant to this article.

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SUPPLEMENTAL ONLINE MATERIAL

Supplemental material can be found online at https://www.mcpdigitalhealth.org/. Supplemental material attached to journal articles has not been edited, and the authors take responsibility for the accuracy of all data.

Abbreviations and Acronyms: **3D-DOSS,** 3-Dimensional Disease Outbreak Surveillance System; **ARI,** acute respiratory illness; **COVID-19,** coronavirus disease 2019; **CPE,** carbapenemase-producing *Enterobacteriaceae*; **eHIntS,** Electronic Health Intelligence System; **HAI,** health care–associated infection; **HCW,** health care worker; **HO,** health care–onset; **IHiS,** Integrated Health Information System; **KPC,** *Klebsiella pneumoniae* carbapenemase; **RTLS,** Real-time Locating System; **SCM,** Sunrise Clinical Manager; **SGH,** Singapore General Hospital

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