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CASE STUDY

Using Machine Learning to Reduce Burden on Infection Control Staff

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Surveillance of health care–associated infection (HAI) is the foundation of infection control and one of the first steps in infection prevention. Traditionally, however, surveillance is performed by infection control professionals (ICPs) who manually review patients' records, searching for defined criteria. Such an approach leaves room for subjective interpretation, resulting in low interrater reliability. Moreover, depending on the surveillance method used — for instance, a search based on antimicrobial results — it may have low sensitivity. In Brazil, leaders at Tacchini Hospital and Qualis, a startup that offers infection control advisory and antimicrobial stewardship, have developed a machine-learning–algorithm robot that has been demonstrated to be a reliable tool for identifying patients with HAIs using a semiautomated method. The performance of this infection surveillance assistant (ISA) robot shows optimal sensitivity, specificity, accuracy, and negative predictive values, and the precision (positive predictive value) is acceptable. The ISA robot identified more patients with HAIs than did the infection control manual surveillance reference. The time spent on patient review was also reduced compared with that spent on manual surveillance. The robot detected HAI in one of every two or three patients reviewed in the interface. The years of the Covid-19 pandemic have highlighted the problem of the shortage of health care professionals, including ICPs. Tacchini Hospital and Qualis aim to increase infection control efficiency, enabling these professionals to spend more time on inpatient wards, implementing care bundles, than handling office activities, such as manual surveillance. In this study, the authors describe the implementation of semiautomated surveillance in a single center, but expanding the

model for different patient scenarios and multiple centers should be the future for external validation of machine-learning surveillance. Such models have the potential for generalization because they do not depend only on fixed rules for HAI classification, but they can also learn from data sets in different patient population settings.

KEY TAKEAWAYS

- The project was driven by infection control professionals (ICPs), who are key to health care–associated infection mitigation. This enables the efficiency and effectiveness of the development and deployment of such an effort.
- The augmented intelligence provided by the infection surveillance assistant (ISA), an artificial intelligence robot, supports the ICPs, enabling them to dedicate more hours to higher-skill patient care delivery.
- A multidisciplinary team, including the hospital's ICPs (*local* team members) and the Qualis team's infectious disease physicians, nurses, pharmacists, and IT experts (*central* team members), should be involved in the effort. This facilitates sharing of the difficulties faced during the journey (research, implementation, and deployment phase), and the solutions and new ideas.
- An explanatory machine-learning model (random forest) and an easy-to-use interface are critical components for model explanation and health care workers' acceptance.
- The implementation of the ISA robot has had no adverse impact on full-time-equivalent staffing for infection control, but it has enhanced care delivery by enabling ICP staff to be more present on the hospital wards performing on-site training and practices validation.

The Challenge

Tacchini Hospital is a general 251-bed hospital for clinical and surgical care in Brazil's southernmost state of Rio Grande do Sul. It serves a region of approximately 400,000 people; it has more than 11,000 admissions per year, and more than 16,000 surgical procedures are performed in the hospital each year. The hospital has two ICUs, one for clinical patients and one for surgical patients, totaling 30 beds (26 beds for clinical and four beds for surgical patients). The hospital attends medium- and high-complexity patients for all clinical specialties and executes surgical procedures for general surgery, pediatric surgery, gynecology, mastology and obstetric surgeries, oncology, neurology, traumatology, plastic, vascular, and urology surgeries. The institution has its research center, called Instituto Tacchini de Pesquisa em Saúde, to support the hospital and researchers in clinical, epidemiological, and innovative project studies. Qualis, located in Porto Alegre, State of Rio Grande do Sul, is a startup in the field of infection control, antimicrobial stewardship, and patient safety that has been working to prevent infections and antimicrobial resistance through telemedicine in more than 30 hospitals in Brazil for more than 10 years.[1,2]

The hospital infection control team has two infection control nurses and an infectious disease physician responsible for coordinating and executing infection control practices. Manual health care–associated infection (HAI) surveillance is performed on the basis of microbiological laboratory results. In addition, they identify antibiotic prescriptions and invasive procedures as indicators for a case review. This method may have low sensitivity (approximately 70%) and does not consider all inpatients. Global HAI surveillance is a laborious process; it is time consuming and, in most centers, is manually executed.[3] For a 251-bed hospital, the infection control team, collectively, would have to devote 45 hours per week to global surveillance or at least 36% of all contracted infection control professionals' (ICPs') time[4,5]; this would demand more than one ICP exclusively for HAI surveillance. Beginning in 2018, before the pandemic, hospital leaders aimed to improve infection control staff services and patient safety, implementing an accurate global hospital infection surveillance without increasing the full-time equivalent of the infection control staff and, if possible, reducing the time spent on manual surveillance. This could optimize human resources and improve bedside activities by the infection control team by reducing the time they spend on manual surveillance.

The Goal

Since January 2017, Qualis has had a partnership with Tacchini Hospital with respect to infection control consultation and antimicrobial stewardship work. This relationship made it possible to construct alternatives to manual surveillance. We needed to implement automated surveillance of HAIs in the hospital. We conceived a multiphase process: study, interface construction, implementation, deployment trial phase, and formal adoption.

First, we aimed to develop an application programming interface (API) for daily data extraction from health care records for machine-learning (ML) HAI classification. Second, we wanted to construct an online interface for ICPs to navigate and classify infections in a semiautomated process (manual confirmation of automated probability results). Third, we would train ICPs to understand ML results and classify infections on the interface. Finally, we would analyze the performance and time results for classification in real-life scenarios before formally adopting the process as the new standard. (For more details on the project elements and timeline, see Appendix Exhibit A.)

The Execution

The partnership with Qualis was key in developing alternatives to manual surveillance. After identifying the need for improving surveillance in conjunction with the hospital's infection control team and establishing a partnership with Tacchini Hospital Research Institute to develop research on ML and HAI surveillance, we began the process. The study phase successfully achieved acceptable results in terms of performance of the model, feasibility, local ICP staff acceptance, and validation of the results. The implementation phase included new data collection, validation based on new data entry, supervised ML, interface development, and training of the hospital infection control team. Scrum methodology was used for project management to develop the systems (new data ML and Web interface).

“ *We developed centrally structured semiautomated surveillance, in which the determination of HAI status was a combination of ML automation results and human confirmation of HAIs by navigating the ISA robot interface.”*

We developed centrally structured semiautomated surveillance, in which the determination of HAI status was a combination of ML automation results and human confirmation of HAIs by navigating the infection surveillance assistant (ISA) robot interface. Low-probability patients (less than 50%) were considered free from HAI (high negative predictive values), and medium (50% or more to less than 75%) or high-probability (75% or more) patients underwent review and classification to determine HAI status.[6] In a centralized system, the responsibility for algorithm creation and adjustments lies with a coordinating center, which is also responsible for local IT support and validation of data collection sources.[7] Validation of HAI surveillance results by the model was also centralized in the coordinating center. The local hospital infection control team performed their own independent surveillance during the deployment phase.

Data Collection

Data collection was structured by searching hospital electronic health records (EHRs) for information relevant to HAIs (information retrieval): laboratory results, radiology results, health care professional records, antimicrobial prescriptions, vital signs, and invasive procedures. All data were built into the model. The bridging among information retrieval (finding HAI criteria in unstructured EHR data), structured data (laboratory examinations, vital signs, and antimicrobial prescriptions), and ML was made possible by the data integration module. This process was intended to extract data in an auditable and standardized way to integrate the hospital and the coordinating center. While executing queries specifically adapted to the hospital database, the module runs periodic (daily) extractions of previously defined data sets among the parties involved. (For more on data extraction and validation, see Appendix Exhibit B.) The developed queries were integrated into the module and made available in its repository, allowing the data holder to view its resources and validate which data were obtained. In this process, information was deidentified (i.e., we eliminated data that could identify patients).

Data quality was first assessed in the previously published study hospital database.[8] We ran a descriptive statistic of the whole data bank, searching for implausible values (based on experts' experience), errors, duplicates, missing data, and outliers. During the implementation and deployment phases from July 2020 to December 2021, we could again confirm data quality and check data, especially for the same parameters as above.[9] For example, during the 6 month deployment phase, for 250,000 temperature results, we found 88 suspicious outliers (0.4 of 1,000 outliers for temperature results).[10] We also created a dashboard for data counting at this stage, and we could compare data with historical controls. After that, developing a daily data pipeline using SQL and Python specifications enabled the ISA robot to query hospital databases with automatic validation by statistical metrics. The report results included the data distribution for each variable, maximum and minimum values, missing values, duplicates, date and time frequencies, total case counts for infection, and other validation checks plots available within ISA's dashboard.

Data Storage Process

After the data were collected, they were stored in a PostgreSQL database located in a cloud service. Every piece of information from the collected data had its types and structure verified in terms of valid data, detection of outliers, and plausibility of data.[7] Then it was stored in the database, allowing these health records to be ready for the preprocessing stage.

Preprocessing Stage and ML

In the preprocessing stage, data entered a pipeline to be prepared for ML purposes. We used the random forest model for the next sprouts of supervised learning. The original algorithm was trained and validated with data content from January 2017 to December 2017 and from January 2018 to July 2018.[8] For implementation and deployment purposes, we updated training and validation with data from 2018 and 2019, and the results of this data training were reported in July to October 2021. For November and December 2021 performance, the model was again trained and validated with data from January to October 2021, and we reviewed the original algorithm features of importance for the model. Risk factors for ventilator-associated pneumonia (VAP), health care–related pneumonia, tracheobronchitis, surgical site infection (SSI), central line–associated bloodstream infections, and catheter-associated urinary tract infections were reviewed from the medical literature and included as new features. Furthermore, for the decision-making process, it was important that the classifiers were well calibrated. We used the postprocessing standard nonparametric isotonic regression calibration for these months.[11]

> *"The timeline is the heart of the ISA interface because it presents all of the information needed for the case evaluation, considering the time as one dimension."*

The Interface

The ISA interface was designed to make HAI classification easy and intuitive. The Web-based platform contains all of the steps the ICP performed manually. For this purpose, the IT chief of development (Tiago Andres Vaz) went on site to observe, learn, and discuss the process of manual surveillance of HAIs with infection control staff. All of the information that needed to be manually searched by nurses, on the basis of National Healthcare Safety Network (NHSN) criteria, was shadowed by the IT chief of development. After that, this information served as the base for the interface modules (Figure 1, Figure 2).

FIGURE 1

Infection Surveillance Assistant Timeline Interface Module

This interface module is designed to help infection control professionals identify patients who may be at high probability for infection. Variables of interest are listed vertically at left, and the horizontal rows display associated status over time. The colors signify the infection probability level based on infection criteria retrieved or other relevant factors, such as changes in test results.

Source: The authors

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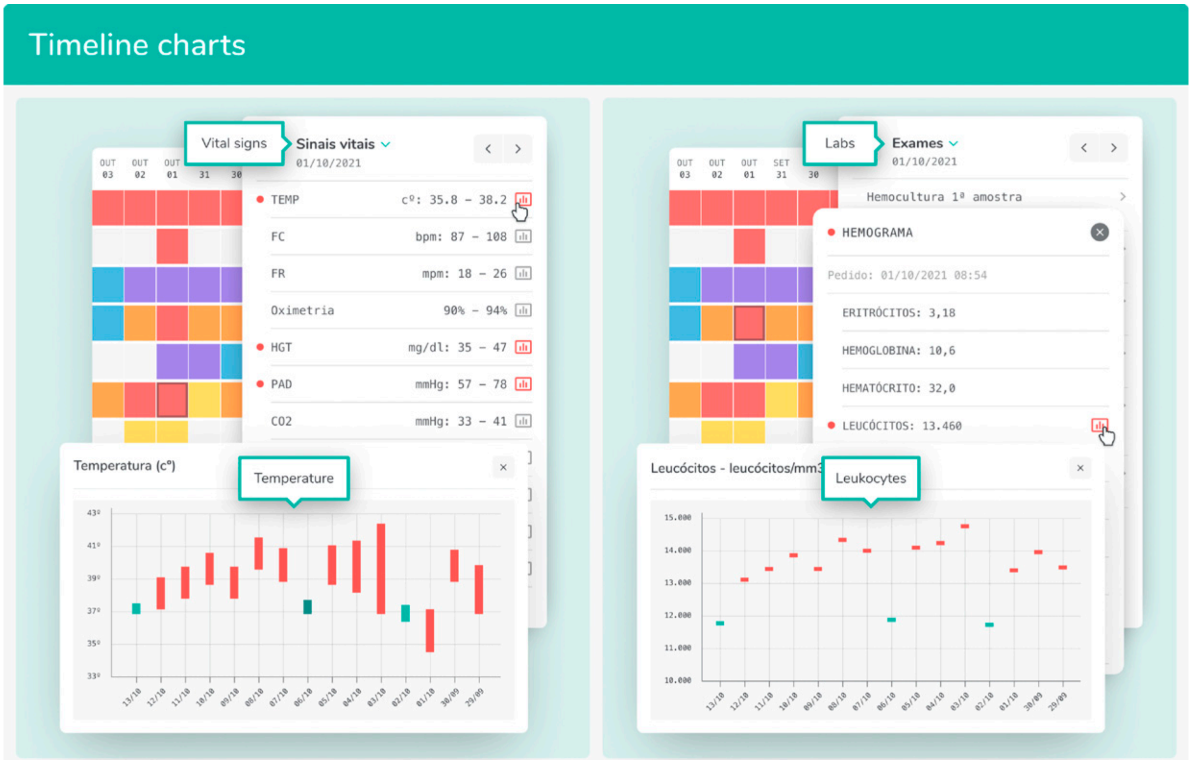
FIGURE 2

Infection Surveillance Assistant (ISA) Timeline Charts

In addition to color-coded cues, the ISA interface provides access to more detailed information retrieved from health care records, such as clinical notes, laboratory examinations, antimicrobials, vital signs, invasive procedures, and radiologic examinations. For some criteria, graphical variation reveals the status throughout hospitalization.



FC = heart rate, FR = breathing rate, HGT = blood glucose test, PAD = diastolic blood pressure, TEMP = temperature.
Source: The authors

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Patient Timeline

After assessing a patient from the HAI probability list, the ICP encounters the patient timeline (Figure 1, Figure 2). The timeline is the heart of the ISA interface because it presents all of the information needed for the case evaluation, considering the time as one dimension. Each day (*x*-axis) is defined by colors depending on the criteria identified, with the hot shades (red and orange) indicating important information related to an HAI classification. For example, in Figure 1, in the first line, which addresses the probability of HAI, the red represents high probability, orange is medium probability, and yellow is low probability. For microbiological and laboratory results, the red color in this line indicates that there is a positive culture, the orange color indicates a negative culture, the yellow color shows altered results for other examinations, such as leukocytes, and the blue color means that the examinations are not altered. For vital signs, the red color represents patients with fever and the orange color any alteration in the other vital signs, such as heart rate, respiratory rate, and blood pressure. Each line (y-axis) represents the probability of HAI (first and second lines) and the information retrieved from health care records — clinical notes, laboratory examinations, antimicrobials, vital signs, invasive procedures, and radiologic examinations. Furthermore, for vital signs and some laboratory examinations, the ISA shows graphical variation throughout the days of hospitalization.

Deployment and Training of Local Staff

The deployment phase was performed from July 2021 to December 2021. For practical deployment of the surveillance system, we started by demonstrating the tool to the hospital infection control team in detail and providing a simulation experience for them to become familiar with the design and patient classification status. This user test did not contain any patient identification. After a week, we had another meeting, at which any questions about the system could be clarified, and a definitive user status was provided, allowing full access to the system. Now the hospital could start to review patients. During the first 6 months, the hospital still performed manual surveillance, and the Qualis central team independently reviewed the cases presented by the ISA robot. The hospital infection prevention physician performed manual surveillance, and the infection prevention nurse was trained in how to perform semiautomated surveillance in the testing mode of the ISA robot. During this period, meetings were held every 2 weeks, at which patient classifications were discussed and usability improvements were suggested and implemented.

Hurdles

We encountered several challenges during the implementation and deployment phase. We changed the data set integration process, which required learning how to integrate data daily. During our study project, we included data retrospectively at just one point in time. We received all data for the previous years (January 1, 2017 to June 30, 2018) and 122,261 patient records and created the data set. The data were validated, and model training was implemented. For the implementation phase, we developed an API to integrate data daily. This API led to some functional problems related to missing data, so we had to create a daily data validation to ensure that we received all of the information set in our application. HAI surveillance is most commonly executed every month. Daily data integration enables us to implement rapid point data error correction; this way, data have already been validated at each monthly semiautomated surveillance.

> *“HAI surveillance is most commonly executed every month. Daily data integration enables us to implement rapid point data error correction; this way, data have already been validated at each monthly semiautomated surveillance.”*

Changes in data structure or new administrative data (creation of another ward or changing ward denomination) were the main challenges we had. These data changes resulted in missing information that decreased algorithm performance. Constant data monitoring, auditing, and validation are crucial for model performance, to increase acceptance by health care workers (HCWs) and to provide transparency to the process.

The Team

Several teams were involved in the project:

- **Qualis Team (central team).** Included members representing nursing, IT, artificial intelligence (AI), pharmacy, and two infectious disease physicians. This team was involved in all aspects of the project: planning, data modeling construction, data queries, data extraction and storage, data integration module adjustments, ML model construction, ML results analysis and performance, results documentation, ISA robot interface construction, ISA robot training for the hospital infection control team, performance analysis during implementation, ML model tuning, and ISA robot interface adjustments.

- **Hospital Infection Control Team (local team).** Included a nurse and an infectious disease physician. This team was involved in planning, ML data analysis and performance, results documentation, ISA robot training for the hospital infection control team, performance analysis during implementation, and ISA robot interface adjustments.

- **Quality Improvement and Safety Team.** Included a quality manager and a member of the hospital IT team. This team was involved in data queries, data extraction, data integration module adjustments, implementation planning, and ISA robot interface adjustments.

Separately, we contracted with another party, Weef Interativa (weef.com.br), to construct the ISA interface. We met weekly through 2020 and 2021 to build and adjust the interface.

Metrics

As mentioned above, during the deployment period (July to December 2021), manual and semiautomated surveillance were performed. The local hospital infection control team executed manual surveillance, and the semiautomated search using the ISA robot was performed by the Qualis central unit. Because we had no recent data on the performance of surveillance by the robot — only the data from the original article (sensitivity, 88.5%; specificity, 78.7%; positive predictive value [PPV], 8.9%; negative predictive value [NPV], 99.7%; and accuracy, 79.0%)[8] — we compared both teams' results in terms of sensitivity, precision, and other metrics every month after the local hospital team had identified the standard reference infections (Table 1, Table 2).

The hospital infection control team who performed manual surveillance was blinded to the ISA robot results. The Qualis central team reviewed the cases of medium and high infection

Table 1. Performance of Infection Surveillance Assistant Robot, Deployment Period, July 2021–December 2021

	Sensitivity (%)	Specificity (%)	PPV (%)	NPV (%)	Accuracy (%)
July	87.5	99.2	83.3	99.4	98.6
August	92.9	99.0	72.2	99.8	98.8
September	84.2	98.8	81.4	99.0	97.9
October	81.2	97.8	54.2	99.4	97.3
November	100.0	95.9	48.0	100.0	96.1
December	92.9	97.8	63.9	99.7	97.6

These data represent the performance of the infection surveillance assistant robot in identifying health care–associated infection compared with manual surveillance (reference standard). PPV = positive predictive value, NPV = negative predictive value. Source: The authors

probability from the ISA robot platform. Manual surveillance was considered the reference standard for comparison.

From July 2021 to December 2021, 6,713 admissions for 6,296 adult patients (59.0% women; median age, 55 years) were recorded. These patients were admitted through the emergency unit (n = 2,961; 44.1%), the surgical department (n = 1,500; 22.3%), the obstetric service (n = 1,055; 15.7%), clinical and surgical units (n = 747; 11.1%), the ICU (n = 104; 1.5%), and other units (n = 327; 4.9%). From these admissions, 321 infections were identified by the ISA robot (4.8%; one infection per 21 admissions) and classified by the ISA robot as follows: urinary tract infections (n = 74; 23.1%), VAP (n = 70; 21.8%), tracheobronchitis (n = 53; 16.5%), pneumonia (n = 49; 15.3%), SSI (n = 38; 11.8%), bloodstream infections (n = 31; 9.7%), and others (n = 6; 1.9%). These rates are higher than the pre–Covid-19 Centers for Disease Control and Prevention's reference of one infection per 31 admissions[12] or previous surveys (3.2%–4.0%).[13,14]

The main parameter we searched for was high sensitivity (80% or more, acceptable; 90% or more, optimal).[8] For ISA robot acceptance and incorporation, we had to improve sensitivity to

Table 2. HAI Cases Identified by ISA Robot, Deployment Period, July 2021–December 2021

	No. of HAIs (Standard)	No. of HAIs by ISA (missed cases; additional cases)	Records Reviewed by ISA (% of Total Hospitalized Patients)	Total No. of Hospitalized Patients	NNS
July	35	42 (−5; +7)	132 (13.5)	975	2.8
August	26	36 (−2; +10)	114 (10.7)	1,061	3.1
September	48	59 (−9; +11)	137 (13.3)	1,029	2.3
October	26	48 (−6; +22)	94 (8.8)	1,069	1.9
November	36	75 (−0; +39)	172 (15.7)	1,089	2.3
December	42	61 (−3; +22)	114 (10.6)	1,073	1.9
TOTAL	213	321 (−25; +111)	763 (12.1)	6,296	2.4

These data represent the performance of the infection surveillance assistant robot in identifying health care–associated infections, compared with the reference manual surveillance in terms of absolute number of infections and the number needed to screen to find one case. HAI = health care–associated infection, ISA = infection surveillance assistant, NNS = number needed to screen (records reviewed by ISA divided by the number of HAIs by ISA). Source: The authors reduce the chance of missing cases. During the deployment phase and new data inclusion for ML, we achieved consistently higher performance in terms of sensitivity, specificity, PPV, NPV, and accuracy — even better than the actual published results, especially specificity and precision (PPV), which improved from 78.7% to 98.0% and from 8.9% to 65.4%, respectively.[8] As mentioned above, the last supervised training, which included data from 2021, new HAI features, and isotonic regression calibration, improved the model's performance (Table 1). Periodically updating the ML models is essential for keeping or improving performance. A model can underperform over time as clinical patterns or patient populations change (e.g., patients with Covid-19) between the data set with which it was developed and the current data with which it is deployed (the *data set shift* concept).[15] Thus, monitoring inevitable data set shifts is part of building reliable ML tools. Furthermore, models can improve over time because of better ML methods or increased data set size.[16]

With regard to the number of HAIs identified by the model, it classified 111 more infections (missed 25) than those by manual surveillance. Semiautomated surveillance performed a global search on approximately 1,000 patients every month. During the 6-month period, the AI algorithm signaled 12.1% of patients for review in the ISA platform from the total number of patients. For 2.4 patients screened (number needed to screen), one had a true HAI (Table 2). The Qualis central team calculated the monthly time for patient review from July to October 2021, and the hospital team calculated the manual surveillance time over 1 month. The time for manual surveillance was approximately 30 hours per month. The mean time spent screening patients was 522 minutes (minimum 390 to maximum 768 minutes) per month (8.7 hours) for automated surveillance (71% reduction).

> *"During the deployment phase and new data inclusion for ML, we achieved consistently higher performance in terms of sensitivity, specificity, positive predictive value (PPV), negative predictive value (NPV), and accuracy — even better than the actual published results."*

After the periodic adjustments in queries and the enhancement of the ML model in November, we ran another validation on the whole data set (July to December 2021). The ML model missed nine cases compared with the 25 losses using monthly validation. Therefore, the final model performance improved to 97.0% sensitivity, 98.2% specificity, 66.7% PPV, 99.9% NPV, and 98.1% accuracy.

One limitation is that the reference standard, or the gold standard, for HAI classification relies on manual methods. Manual surveillance is based on fixed criteria and depends on human subjectivity and willingness to search for a vast amount of data.[3] The method may sometimes have interrater or methodology variability, with poor sensitivity results.[17] Ideally, this variability could be reduced by classification by a panel of independent experts, although they would also suffer from fatigue from EHR review, especially in global surveillance. Despite that, the ML model outperformed the hospital standards. It was based on ML features of importance chosen by the model and infectious diseases experts' inputs (Appendix Exhibit C). When these features are revised and validated periodically, the model's generalizability is increased, because it does not depend on fixed rules for HAI classification. Furthermore, the convenience of private cloud services and the ML algorithms developed as open-source software might leverage the replication of ML models.

We reviewed the nine cases missed by the model: two patients were not supposed to be searched; two patients were missing information in the EHR; ML identified two patients who were not selected because of interface problems; and three patients had evidence of HAIs, but ML had classified it as a low probability.

Of that group of nine missed patients, the two patients who were not supposed to be searched were in ambulatory care, and the robot was set to search only admitted patients. Both patients had a bloodstream infection from the dialysis clinic. One patient was classified by the local hospital ICP team on the basis of a laboratory culture result (urinary tract infection) that was not included in the EHR of the hospital (laboratory result on paper). Another patient was classified as having a low probability by the model but was diagnosed by the local team as having tracheobronchitis. He had a productive cough, tachypnea, hypoxemia, and *Staphylococcus aureus* on a respiratory tract culture. The robot missed the case because of the lack of clinical note information in the ML model. By August 2021, the hospital had created a new structured formulary to include clinical notes, and it was being tested in that patient's specific unit. This information was not programmed to be captured by our queries at the time.

The algorithm classified two patients as high probability for infections, but they were not selected for semiautomated surveillance confirmation because of interface problems. Both had long durations of hospital stay; one had VAP, pneumonia, and tracheobronchitis, and the other had VAP and a urinary tract infection.

Another patient, a 35-year-old woman who presented with dysuria and a positive urinary culture, was classified by the robot as low probability (true missing by the algorithm).

Finally, the model missed two patients with SSI. One patient, a 60-year-old woman, was admitted on September 27 for a surgical procedure of spine arthrodesis due to a herniated disc. She was discharged on October 1. Thirteen days later, she returned to the hospital with drainage from the surgical incision and fever. The secretion culture revealed *Staphylococcus aureus* infection.

The other patient with SSI was an interesting case. The patient was a 49-year-old woman admitted on December 15 for a hysterectomy for endometrial hyperplasia. She stayed in the hospital for 1 day, was discharged, and returned 7 days later (December 22) with fever and abdominal pain. She was started on antibiotics (cefuroxime and metronidazole). Her computed tomography scan showed pelvic liquid collection, and she underwent another surgery for diagnosis and drainage on December 24. The surgical diagnosis was a purulent pelvic abscess, and the culture results found *Escherichia coli*. The pelvic abscess was drained, and the patient had clinical improvement and was discharged on December 25. This patient met the NHSN criteria for an SSI (fever, positive culture results, and imaging results demonstrating the site of infection). However, the case was misclassified as having a low probability of disease (35% chance of HAI). Why did this happen? In both cases of SSI, because of the short length of stay (LOS), the symptoms did not appear until after discharge.

HAI risk is a time-dependent event. The greater the LOS, the higher the risk. Hauck and Zhao[18] found that, for each additional night in the hospital, there is an increased risk of infection of 1.6%. The use of invasive procedures and time on devices are other known risk factors for a time-dependent HAI. This could be partially explained by underlying morbidity and a more significant observation period of prolonged hospital stays.[19,20] In addition, one of the main features of importance for infection from our random forest classification model is LOS (see Appendix Exhibit C). We see that more patients with HAIs had a longer LOS. Therefore, we hypothesize that for this patient, who had zero days since admission to showing signs of infection and stayed in the hospital for only 4 days, the system misinterpreted the case as a low probability because of a kind of selection bias or informative missingness due to the low level of data in the EHR over time.[21]

As of January 2022, the infection control team is using only the ISA robot for HAI surveillance. During January and February 2022, the HAI rates increased by 42%. The median infection rate in 2021 was 9.3 infections per 1,000 patient-days. In January 2022, the infection rate was 16.4 infections per 1,000 patient-days (compared with January 2021, when it was 9.2 infections per 1,000 patient-days), and in February 2022, it was 15.8 per 1,000 patient-days (compared with February 2021,when it was 8.7 infections per 1,000 patient-days).

This increase in HAIs represents the capacity of the robot to identify more patients with infection criteria than can manual surveillance. The ISA robot identified 111 more infections and missed only three in 6 months. We are in constant contact with the hospital infection control team (our collaboration continues), and we are still monitoring ISA robot results. The hospital did not report any outbreak of infections or any other change in hospital routine to explain this increase; as the hospital increases its capacity to search and find HAIs using the ISA robot, we would expect such increases.

> “*The final model performance improved to 97.0% sensitivity, 98.2% specificity, 66.7% PPV, 99.9% NPV, and 98.1% accuracy.*”

Infection surveillance and a well-established, risk-based infection-prevention strategy are core measures for patient safety and quality of care. Using active surveillance methods with high sensitivity that are feasible to apply and that can search for all kinds of infections and patients is one step toward quality and infection elimination. These pandemic years have highlighted the challenges we may face in health care: patient overload, understaffing, emerging infection transmission and bacterial resistance, increase in HAIs, and the central role of ICPs. Interpretation of data coming from surveillance is essential for planning, implementation, and evaluation of strategies for infection reduction. Innovative methods of surveillance can enable accurate infection review, minimize the time for HAI diagnosis, and improve ICP efficiency. Poor HAI surveillance produces a low quality of care.

Where to Start

For organizations looking to undertake such an initiative, we offer several factors for consideration.

First, recognize that HCW acceptance is crucial for innovative initiatives. Adoption of innovation is a challenge in most in health care settings where it can directly impact people's lives. In an HCW-driven project, the connections between parties and the trust constructed are the basis for the project's success. The development of the ISA robot was based on transparency, shared information and knowledge, and motivated teams who trusted each other. During the implementation and deployment phases, the whole team presented and solved the problems.

Next, understand that acceptance will come in stages. The project planning, itself laid out in phases, facilitated acceptance. At first, the parties agreed to test and evaluate the ML algorithm. The specialists in infection control approved the ISA robot algorithm performance on the basis of epidemiology-accepted metrics. These results were peer reviewed and published. An easy-to-use and self-explained interface for ICPs to use to evaluate patients is critically important in enabling the ICPs to see the value and accuracy of the model as they evaluate patients.

Finally, be sure to maintain a rigorous process for retesting and validating the ML algorithm and the interface in a real-world situation, together, during the implementation and deployment phase; this will instill confidence and build acceptance by demonstrating performance improvement. In January 2022, we deployed the system for the hospital ICPs' use.

This is an implementation of automated surveillance in a single center; expanding the model to different patient scenarios and multiple centers should be the future for external validation of ML semiautomated surveillance. These ML models have the potential for generalization because they do not depend on fixed rules for classification and can learn from data set in different patient populations.

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Appendix

Development of an Infection Surveillance Assistant Robot to Mitigate Health Care–Associated Infections

Disclosures: Stephani Amanda Lukasewicz Ferreira, Arateus Crysham Franco Meneses, Tiago Andres Vas, Otávio Luiz da Fontoura Carvalho, Camila Hubner Dalmora, and Rodrigo Pires dos Santos are members of Qualis. Daiane Pressoto Vanni, Isabele Ribeiro Berti, Fabiane Rocca, and Márcio Pereira Ramos have nothing to disclose.

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