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Editorial

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Biomedical and health informatics continue to contribute to COVID-19 pandemic solutions and beyond

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As I write this editorial in May of 2021, there are broad indications of reopening and decreasing COVID-19 pandemic restrictions in the US, while there are major pandemic hotspots globally. Like many others, I am hopeful that the lessons from the pandemic can be applied to major public health issues in the future. How transferrable are the theories, models, algorithms, and informatics-based solutions that we've developed? Through the years, we've certainly argued that this is a fundamental characteristic of informatics as a scientific field. I highlight 5 COVID-related studies in this issue, and I ask you to reflect, as I have done, on the key lessons for the future.

In partnership with state and local public health agencies as well as health systems, Dixon et al describe the development and implementation of population-level dashboards that are deployed on top of a statewide health information exchange.[1] Two dashboards collate information on individuals tested for and infected with COVID-19. The primary dashboard enables authorized users working in public health agencies to monitor populations in detail. In contrast, a public version provides higher-level situational awareness to inform ongoing pandemic response efforts in communities. Over the span of 2 months, the dashboards were accessed by 74 317 distinct users, indicating substantial use. In terms of usefulness, the private dashboard enabled detection of a local community outbreak associated with a meat-packing plant. The authors call for continued investment in a statewide health information exchange as a critical component of public health infrastructure.

Klann and co-authors describe the development and validation of a computable phenotype for COVID-19 severity by the Consortium for Clinical Characterization of COVID-19 by EHR (4CE).[2] 4CE is an international collaboration that is addressing COVID-19 through federated analyses of electronic health record (EHR) data. They developed an EHR-based severity phenotype, consisting of 6 code classes using patient hospitalization data, and validated the phenotype in twelve 4CE international sites against the outcomes of intensive care unit admission and/or death. The full 4CE severity phenotype developed by experts had a pooled sensitivity of 0.73 and specificity 0.83 for the combined outcome of intensive care unit admission and/or death; however, the sensitivity of individual code categories for acuity had high variability. The authors also conducted a pilot in 1 site in which they compared selected predictors of severity between a machine learning approach and the 4CE phenotype with mean areas under the curve reported as 0.956 (95% confidence interval, 0.952–0.959) and 0.903 (95% confidence interval, 0.886–0.921), respectively. The authors suggest that the severity phenotype comprising 6 code classes was resilient to coding variability across institutions, but they raised the concern that machine learning approaches may overfit hospital-specific orders. These findings contribute to the literature about generic vs institution-specific approaches.

Malden, Heeney, Bates, and Sheikh conducted a qualitative study to develop an in-depth understanding of how hospitals with a long history of health information technology (HIT) use responded to the COVID-19 pandemic from an HIT perspective.[3] Informed by a topic guide, they interviewed 44 healthcare professionals with a background in informatics from 6 hospitals internationally via videoconference. They applied thematic analysis to develop a coding framework and identify emerging themes. This resulted in 3 themes and 6 subthemes.

Key findings included (a) HIT was employed to manage time and resources during a surge in patient numbers through fast-tracked governance procedures and the creation of real-time bed capacity tracking within EHRs; (b) improving the integration of different hospital systems was important across sites; (c) use of hard-stop alerts and order sets was perceived as effective in helping to respond to potential medication shortages and select available drug treatments; (d) use of information from multiple data sources to develop alerts facilitated patient treatment; and (e) risk of nosocomial infections was reduced through upscaling/optimization of telehealth and remote working capabilities. Because of these changes, informaticians felt more valued by hospital management than prior to the COVID-19 pandemic. All study findings have relevance for the future application of HIT along with informatics expertise to address other significant public health concerns.

Given that the requirements for facial mask wearing are decreasing, particularly for those who have completed their COVID vaccination course, what can we learn from 2 papers in this issue that focus on the topic of facial masks? He et al analyzed a total of 771 268 US-based tweets from January to October 2020.[4] They first developed machine learning classifiers to identify and categorize relevant tweets and subsequently performed a qualitative content analysis of a subset of the tweets to understand the rationale of those who opposed mask wearing. Among 267 152 tweets that contained personal opinions about wearing facial masks to prevent the spread of COVID-19, the proportion of antimask tweets stayed constant at about the 10% level throughout the study period. Although negative effects, lack of effectiveness, and being unnecessary or inappropriate for certain people or under certain circumstances, were cited as reasons not to wear masks, such tweets were significantly less likely than promask tweets to cite external sources of evidence to support the arguments. The combination of machine learning classifiers and qualitative analysis to inform health communication offers a method that can be applied to other topics and data sources. Mercaldo and Santone designed a transfer learning approach that exploited the MobileNetV2 model to identify face mask violations using a data set of 4095 images of people with and without masks.[5] They obtained an accuracy of 0.98 in face mask detection. While the study was motivated by the use case of the COVID-19 pandemic, transfer learning approaches are not widely reported in the biomedical and health informatics literature. This study may inspire other applications of transfer learning.

JAMIA has published almost 100 COVID-related papers and will continue to do so, but as always our priority is on innovative and generalizable findings.

CONFLICT OF INTEREST STATEMENT

None declared.

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