110學年度第1學期資訊管理研究所博士班資格考

科目:高等健康資訊學

Time：2021/11/12 14:00-17:00

Format：

After reading the following three abstracts which were cited from the Journal of the American Medical Informatics Association in the year of 2020, please answer the following questions in depth as possible as you can and based on some related theories if necessary.

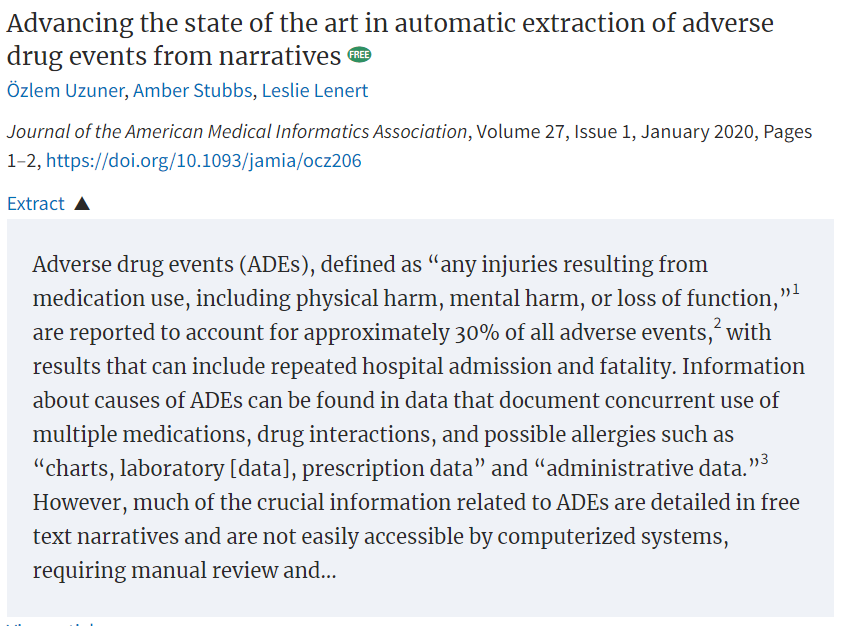
1. What are the differences between epidemic and pandemic? (6 %)
2. What are the differences between the vaccine efficacy and effectiveness? (6%)
3. What are the differences between the cohort study and the case control study? (7%)
4. What are the relationships between the physician burnout and the hospital performance? (7%)
5. What are the relationships between the behaviors of healthcare consumers and healthcare providers? (7%)
6. 請分析近五年Medical Informatics相關重要期刊中，如 Journal of the American Medical Informatics Association與Journal of Medical Internet，智慧醫院的發展趨勢。(33%)
7. Please read the following, what ways has been implemented in Taiwan until now, and against the balancing of the privacy and infection of the COVID-19 pandemic. What is their consideration for each implemented measure? (11%)



1. Data visualization can increase the cognition of the data for human. The following paper used it to create and evaluate the fall-prevention program. Suppose you are the one to generate the data charts. From the data warehouse viewpoint, what charts you can use to perform it, and what data you should collect to prevent the fall events. (11%)



1. The following paper mentioned the narratives can be a vehicle to identify the ADE (adverse drug events). Please guess what narratives in patient record can leak the possibilities of the ADE, and what is the implication of the terms/clauses related to the ADE. (11%)



Journal of the American Medical Informatics Association*, Volume 27, Issue 6, June 2020, Pages 853–859*

Abstract (I)

Objective

To describe the implementation of technological support important for optimizing clinical management of the COVID-19 pandemic.

Materials and Methods

Our health system has confirmed prior and current cases of COVID-19. An Incident Command Center was established early in the crisis and helped identify electronic health record (EHR)-based tools to support clinical care.

Results

We outline the design and implementation of EHR-based rapid screening processes, laboratory testing, clinical decision support, reporting tools, and patient-facing technology related to COVID-19.

Discussion

The EHR is a useful tool to enable rapid deployment of standardized processes. UC San Diego Health built multiple COVID-19-specific tools to support outbreak management, including scripted triaging, electronic check-in, standard ordering and documentation, secure messaging, real-time data analytics, and telemedicine capabilities. Challenges included the need to frequently adjust build to meet rapidly evolving requirements, communication, and adoption, and to coordinate the needs of multiple stakeholders while maintaining high-quality, prepandemic medical care.

Conclusion

The EHR is an essential tool in supporting the clinical needs of a health system managing the COVID-19 pandemic.

本頁為題1~5

Journal of the American Medical Informatics Association*, Volume 27, Issue 9, September 2020, Pages 1401–1410*

Abstract (II)

Objective

The study sought to examine the association between clinician burnout and measures of electronic health record (EHR) workload and efficiency, using vendor-derived EHR action log data.

Materials and Methods

We combined data from a statewide clinician survey on burnout with Epic EHR data from the ambulatory sites of 2 large health systems; the combined dataset included 422 clinicians. We examined whether specific EHR workload and efficiency measures were independently associated with burnout symptoms, using multivariable logistic regression and controlling for clinician characteristics.

Results

Clinicians with the highest volume of patient call messages had almost 4 times the odds of burnout compared with clinicians with the fewest (adjusted odds ratio, 3.81; 95% confidence interval, 1.44-10.14; P = .007). No other workload measures were significantly associated with burnout. No efficiency variables were significantly associated with burnout in the main analysis; however, in a subset of clinicians for whom note entry data were available, clinicians in the top quartile of copy and paste use were significantly less likely to report burnout, with an adjusted odds ratio of 0.22 (95% confidence interval, 0.05-0.93; P = .039).

Discussion

High volumes of patient call messages were significantly associated with clinician burnout, even when accounting for other measures of workload and efficiency. In the EHR, “patient calls” encompass many of the inbox tasks occurring outside of face-to-face visits and likely represent an important target for improving clinician well-being.

Conclusions

Our results suggest that increased workload is associated with burnout and that EHR efficiency tools are not likely to reduce burnout symptoms, with the exception of copy and paste.

本頁為題1~5

Journal of the American Medical Informatics Association*, Volume 27, Issue 12, December 2020, Pages 1834–1843*

Abstract (III)

Objective

Improving the patient experience has become an essential component of any healthcare system’s performance metrics portfolio. In this study, we developed a machine learning model to predict a patient’s response to the Hospital Consumer Assessment of Healthcare Providers and Systems survey’s “Doctor Communications” domain questions while simultaneously identifying most impactful providers in a network.

Materials and Methods

This is an observational study of patients admitted to a single tertiary care hospital between 2016 and 2020. Using machine learning algorithms, electronic health record data were used to predict patient responses to Hospital Consumer Assessment of Healthcare Providers and Systems survey questions in the doctor domain, and patients who are at risk for responding negatively were identified. Model performance was assessed by area under receiver-operating characteristic curve. Social network analysis metrics were also used to identify providers most impactful to patient experience.

Results

Using a random forest algorithm, patients’ responses to the following 3 questions were predicted: “During this hospital stay how often did doctors. 1) treat you with courtesy and respect? 2) explain things in a way that you could understand? 3) listen carefully to you?” with areas under the receiver-operating characteristic curve of 0.876, 0.819, and 0.819, respectively. Social network analysis found that doctors with higher centrality appear to have an outsized influence on patient experience, as measured by rank in the random forest model in the doctor domain.

Conclusions

A machine learning algorithm identified patients at risk of a negative experience. Furthermore, a doctor social network framework provides metrics for identifying those providers that are most influential on the patient experience.

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