UCLA Health

Abstract Form

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Project Title:	Utilizing artificial intelligence for clinical decision support: developing a natural language processing model to risk stratify and prioritize patient portal messages

Research Category (please check one):

☒	**Original Research**	☐	**Clinical Vignette**	☒	**Quality Improvement**	☐	**Medical Education Innovation**

Abstract

Introduction:
In-basket messaging has become an increasingly popular tool for patients to directly communicate with their medical providers. However, the use of this medium has brought new challenges for patient care especially given the significant growth of in-basket messages since the COVID-19 pandemic[1,2]. There is a lack of standardization as to what information is appropriate for patient portal communication and what acceptable response times are. This can lead to the communication of information by patients through the portal that may require more urgent evaluation to prevent significant morbidity[3]. To combat this problem, UCLA developed and deployed a natural language processing (NLP) tool utilizing artificial intelligence (AI) and machine learning (ML) to analyze and risk-stratify patient portal messages. Below, we describe the process of developing the model, initial outcomes, and ongoing interventions to address high-risk patient portal messages in a time-sensitive manner.

Methods:
An AI model utilizing NLP was developed to identify patterns, phrases, and content of patient portal messages that are considered high-risk. Through an iterative stepwise process, the research team analyzed 15,537 total patient portal messages including 1,383 that were considered high-risk per a validated symptom checklist used for triage of patient telephone calls. The NLP model created a predictive algorithm for high-risk features of messages based on a small subset of messages and then iteratively updated the algorithm ("learning") when tested against additional portal messages. The output of the model was a risk score for all patient portal messages received in the primary care setting. Initial interventions have centered around moving high-risk flagged messages earlier in the queue for staff that process patient communications.

Results:
The NLP model was successfully developed by a large AMC. The model achieved a sensitivity of 75%, specificity of 99%, precision of 52%, and accuracy of 99% during a pilot validation of over 15,000 portal messages. The model was then deployed across multiple AMC ambulatory clinics. Scores that exceeded a defined threshold of 0.5 were deemed high risk and were automatically moved to the top of the queue for staff triage. Median turnaround times are being calculated for pilot clinics to determine the effect of the model on provider response to high-risk messages.

Conclusions:
Our insights into developing an NLP model to risk stratify patient portal messages may help inform future efforts for health systems given the relative infancy of using AI and ML as clinical support tools. There are currently no gold standard benchmarks to validate these tools, but it appears appropriate to target sensitivity given the relative consequences of missing false negative messages. Other active research areas include identifying specific symptoms that disproportionately impact risk scores, disposition outcomes from high-risk messages, and longitudinal effects of model retraining. Based on message volume and severity, additional resources may be deployed to handle high messages in real-time including overnight and on weekends. NLP has strong potential to aid patient care and would benefit from further study and nationalized collaboration.