Enhancing Surveillance of Healthcare-Associated Violence Using NLP and Clinical Notes

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OBJECTIVES

❖ Patient and family violent outbursts towards staff, caregivers, or through self-harm, have received greater attention during the ongoing behavioral health crisis. These healthcare-associated violent (HAV) events are likely under-reported, as staff-reporting logs are the only data source being used.

❖ We sought to access the feasibility of using provider handoff notes to identify under-reported HAV events.

We hypothesized that:

❖ HAV related data are embedded in nursing handoff notes.

❖ These data can be mined using Natural Language Processing (NLP) techniques.

METHODS

Our general approach had a few key steps:

Data acquisition:

1. We extracted nursing handoff notes across inpatient units at two hospitals for 2019: a tertiary care center and a community-based hospital.
2. We included notes of all patients < 21 years of age admitted to inpatient units, including the pediatric intensive care unit (PICU) level, and for the community hospital where PICU doesn’t exist, we added neonatal intensive care unit (NICU) notes instead.
3. We have obtained nursing handoff documentation, pain treatment reports, and event reports. We had 70,981 notes from the tertiary care center for model building and internal validation, and then used 19,332 notes from the community hospital for external validation.

Model building and training:

1. We used software-assisted manual review of retrospective data to develop a robust set of training data. Figure 1 presents a screenshot from our GUI – DrT.
2. We then apply this model to the full set of notes and conduct further review to identify safety events of interest.
3. We trained the NLP models on the tertiary care center data and validated it on the community hospital data.
4. Finally, we applied these surveillance methods to real-time data to assess reporting completeness of new cases.

RESULTS

❖ The final community hospital model sensitivity was 96.8% (95% C.I. 90.6-100%) and a specificity of 47.1% (39.6-54.6%) compared to manual review (model performances are presented in table 1)

CONCLUSIONS

NLP-assisted review is a feasible method for surveillance of HAV events, with implementation and usability that can be achieved even at a low IT-resourced hospital setting.

DISCLOSURES

We have no financial interests or relationships to disclose.

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