Engendering Trust and Usability in Clinical Prediction of Unplanned Admissions: The CLinically Explainable Actionable Risk (CLEAR) Model

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Background. Modern machine learning (ML) methods have seen tremendous growth and technical advances in methodology, which have great potential to inform clinical predictions. However, widespread adoption of ML models in clinical practice remain limited due to concerns with performance, trust, transparency, usability, actionability, and ineffectiveness in clinical trials.[1] Unplanned or preventable hospital admissions (PHAs), which cost $17 billion annually for the U.S. Centers for Medicare and Medicaid Services (CMS), are key outcomes that may benefit from ML and were the subject of the recent CMS Artificial Intelligence (AI) Challenge.[2,3] As part of our top 25 submission, we developed the CLinically Explainable and Actionable Risk (CLEAR) model, an interpretable deep-learning model to predict PHAs, and a user-friendly app that presents accurate and actionable predictions while dynamically incorporating clinician feedback.

Methods. The CLEAR model is predicated upon the recurrent neural network (RNN) framework proposed by Liu, et al.[4] for modeling clinical time-series. CLEAR utilizes temporal windowing and dual attention mechanisms to identify important episodes in care, capture complex dependencies, remain robust to challenges with longitudinal observational data, and identify highly-predictive patient features. CLEAR incorporates RNNs, sequence segmentation, clinical concept embeddings, and multiple attention mechanisms to generate patient-level predictions. Output from this technical framework is accessible via an app and is coupled with clinician-feedback to learn the set of features that are clinically actionable. To assess the models' discriminative ability to predict unplanned admissions within 30 days, the CLEAR model (CLEAR-Interpretable) was validated on a 5% subset (2.6 million claims, 78,000 patients) of Medicare data. We calculated the area under the receiver operating characteristic (AUROC) to assess predictive performance.

Results. In our experiments, the CLEAR model without attention ($AUROC_{CLEAR\text{-}RNN} = 0.786$) exceeded the performance of prior models as well as the logistic regression baseline ($AUROC_{LR} = 0.697$). Previously published models that predicted PHA using 2008 CMS claims data demonstrated AUROCs of 0.60-0.63; more recent methods achieve AUROCs of 0.55-0.75.[5] The full CLEAR model with dual attention under-performed the other models in this performance metric but was still in line with prior baselines ($AUROC_{CLEAR\text{-}Interpretable} = 0.626$), demonstrating the tradeoff between interpretability and accuracy.

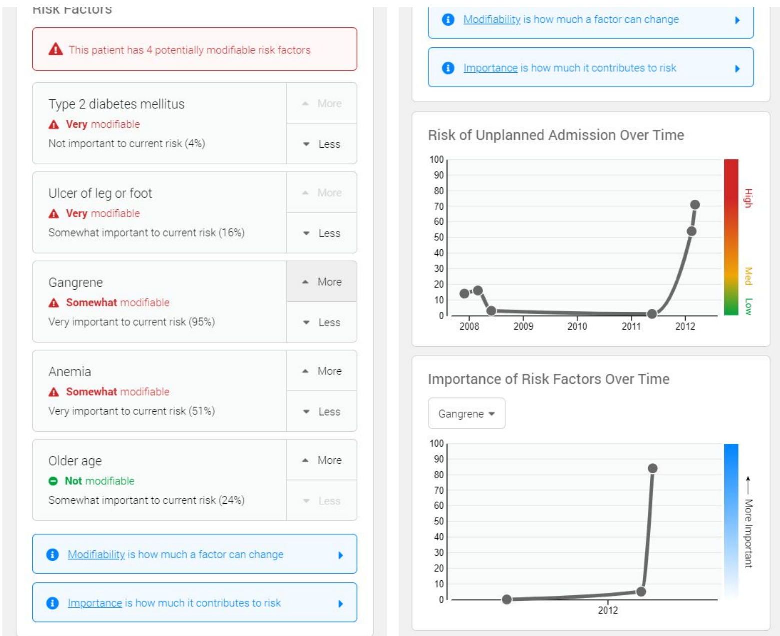

Figure 1. Selected displays of the provider view for a single patient in CLEAR. Left – the list of modifiable risk factors for the patient; Right – graphs that display of risk of PHA over time and importance of selected risk factor (selected via dropdown menu) over time.

Conclusion. CLEAR is an effective method to predict PHAs, with predictive performance that is comparable to or exceeds prior models while promoting interpretability and actionability. In contrast to prior models, CLEAR predicts *any* PHA, which is both more challenging and more generalizable to the larger Medicare population. The dual attention mechanisms in CLEAR and user-friendly, interactive app interface can offer insight to let clinicians look inside the black box and enhance actionability.

References

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