Leveraging data science for optimal follow-up of multimorbidity patients - a research protocol

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1. Background

Multimorbidity (MM) affects over 50 million individuals in the European Union, presenting a substantial challenge to healthcare systems [1]. While promoting preventive care and ensuring continuity of care are advocated to improve patient outcomes, current guidelines offer limited guidance on managing MM patients [2]. Defining time intervals between clinical appointments has significant clinical implications; however, scant evidence is available to assist physicians in determining when to schedule follow-up appointments, particularly for patients with MM. Unplanned hospital admissions serve as indicators of poorly controlled chronic conditions and suboptimal preventive care [3]. Most existing predictive models focus on readmissions or patient selection for specific clinical interventions, leaving the influence of hospital admission prediction on physicians' decision-making largely unexplored [4]. We hypothesize that electronic health record (EHR) data can be useful for predicting unplanned hospital visits for MM patients and that providing physicians with interpretable, real-time predictions may aid in follow-up interval decision-making, ultimately improving clinical outcomes.

2. Methods

We are using a dataset from a single teaching hospital of over 800,000 patients spanning 14 years to develop machine learning models for hospital admission prediction and evaluate their clinical impact. Initial steps included data preparation, collection, verification, and conversion to the Observational Medical Outcomes Partnership (OMOP) common data model. We will explore a self-attention neural network to learn representations of structured patient data, including International Classification of Diseases, Ninth Revision (ICD-9) codes, laboratory results (LOINC), drug prescriptions (ATC), and time stamps of hospital episodes. Learned representations will be used to predict unplanned hospital admissions at different time windows: 7, 30, 180, and 365 days. After internal model validation, we will conduct two clinical studies. The first is an observational study (1) to externally validate model performance and compare its accuracy against physician performance. The second is a clinical trial to evaluate the impact of predictive modeling on clinical decision-making. For this study, we will create a software tool for visualizing personalized risk predictions and their explanations, incorporating attention weights and SHAP values that will randomly be provided to physicians during outpatient episodes. We will measure differences in time to the next appointment, appointment frequency, unplanned hospital admissions, and healthcare-related quality of life between study groups to understand the clinical impact of predictive modeling.

3. Conclusion

The utility of EHR data for predicting unplanned hospital admissions and its potential for informing follow-up interval decision-making in primary care for MM patients remains largely unexplored. By enhancing the evidence base for managing MM patients, our findings can support healthcare providers in delivering more efficient, patient-centered care, and facilitate the optimization of limited healthcare resource allocation. Findings based on our hospital data will illuminate the performance of predictive models for unplanned hospital admission using routinely collected EHR data along with their capacity to inform follow-up interval decision-making for MM patients. Prevalent critiques of machine learning projects in healthcare include the lack of fair comparisons between models and the standard of care, as well as a gap between model results and actionable clinical interventions for healthcare professionals. In this study, we tackle both points by comparing machine learning predictions with physicians' predictions and analyzing the impact of providing clinicians with

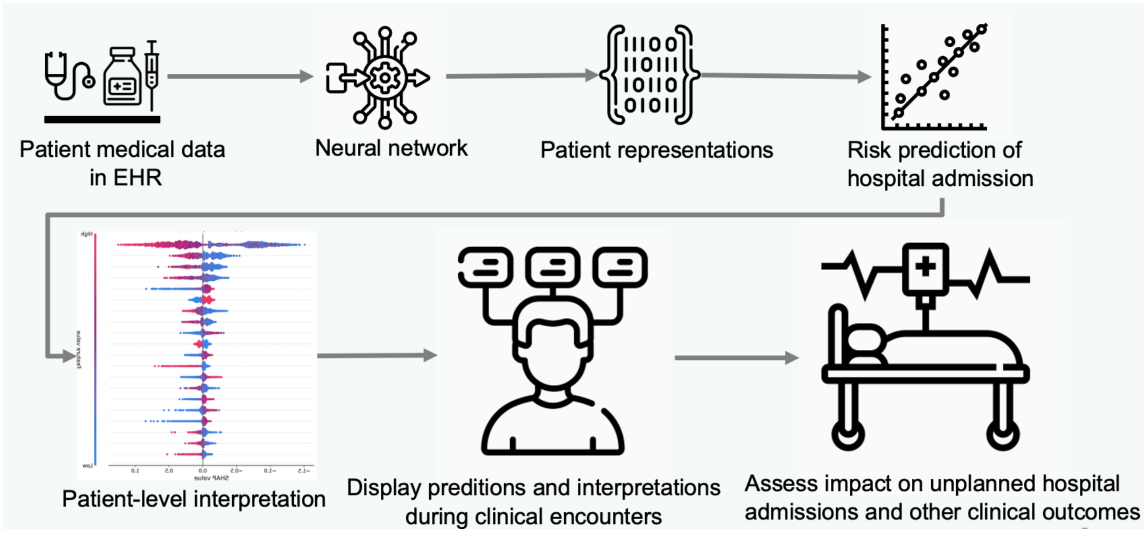

Figure 1: Diagram of the proposed research project

patient-level predictions on their decision-making in situations characterized by considerable uncertainty.

References

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