An Online Clinical Dashboard Prototype for Predicting Postoperative Delirium

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Abstract. Postoperative delirium (POD) as a severe medical condition can result in poor outcomes like dementia or death. Early POD predictions are key to prevent these and should be transparently displayed to medical decision makers. In this demonstration, we explain how a clinical decision support system (CDSS) in form of a clinical dashboard (CD) might look like to early detect POD. We demonstrate an implemented online CD prototype consuming real clinical data on a daily basis. We extract POD relevant data and describe our underlying data model. A previously developed prediction algorithm provides patient specific POD risk assessments. We further show our front-end design comprising relevant vital signs, demographics, predictions, and model performances either on a patient-, or on a population-based level. In the end, we highlight strengths and limitations of our CD prototype.

Keywords. Decision Support System, Prediction Model, Postoperative Delirium

1. Introduction

Postoperative delirium (POD) may result in prolonged hospital stays, mobility impairments, long-term cognitive decline, dementia, or death following increased treatment costs for health facilities [1-4]. Patients experiencing POD suffer from common symptoms like hallucinations, disorientation, and agitation [1]. Delirium guidelines suggest preventive countermeasures like a noise-reduced recovery phase after surgery [2]. Continuous monitoring and predictions of POD onsets at the bedside could help clinicians to identify specific patients at high risks. Additionally, population-based POD incidences and outcomes provide insights for the identification of vulnerable patient groups. Visualizing related electronic health records (EHRs) could leverage an institution-wide POD quality assessment increasing patient safety in the future [3-4].

Authors have stressed on the need for close collaboration between technical and medical experts for successfully implementing a valuable clinical decision support system (CDSS) [5-7]. Previous work also suggested a clinical dashboard (CD) that provides reporting and predictive capabilities with data filtering and drilling options for implementing a CDSS [8]. In this work, we have realized an online CD prototype (consuming real EHRs) fusing technical and medical expertise. We connected our CD to the clinical data infrastructure and ran a simple POD prediction model. We developed visualizations while directly assessing the underlying data availability. Previous work

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highlighted these aspects as key success factors for a CDSS [5]. In this demonstration, we aim to provide insights into the CD prototype highlighting strengths and limitations of the usage in clinical practice. We do not focus on the concrete implementation of the prediction model since we described model training and validation in previous work [9].

2. Technical Implementation

At our clinical institution, a data engineering team is developing and maintaining a data lake (DL) storing and integrating data from clinical information systems. We developed extraction scripts collecting POD relevant EHRs from the DL infrastructure. Extracted data comprised information about hospitalizations, anesthesia procedures, demographics, vital signs, medications, and diagnosis. We demonstrate the basic data extract-, transform-, load- (ETL) pipelines behind this data collection procedure. For storing the extracted data, we set up a PostgreSQL database maintaining five tables in a data model delivering the CD (see Table 1).

Table 1: Description of data tables used by the clinical dashboard prototype

Table Name	Data Content
OP Master	Admission-, surgery time stamps, demographics
Observations	Vital signs, medical device settings, scores
Medications	Given drugs, volumes, bolus or rates
Lab Values	Blood gas values, laboratory test results
Diagnosis	Comorbidities, in-hospital diagnosis

We explain the structure and the relationships of included data tables. We provide filter capabilities of data items relying on our data model design. Our dashboard consumes data between 2021 and the last couple of hours of the current point in time. We demonstrate how ETL scripts update our back-end and present data from either the day of the demo presentation, or the day before. We used the open-source Python framework Dash that provided dashboard design capabilities (like charts or tables) with Plotly for designing the CD front-end. During the demonstration, we show how users can access the resulting web-based CD at our clinical institution.

3. Dashboard Design

We included three basic font-end views in our web-application. Table 2 shows the display contents per view.

Table 2: Description of front-end views

View Name	Detail Level	Display Content
Home	Patient-based	Individual POD predictions, vital signs curves, and in-hospital time stamps
Statistics	Population-based	Age, gender distributions, POD incidence rates over time
Metrics	Population-based	AUROC, false positive and negative rates, additional metrics over time

We provided filters for the responsible medical unit, the organizational unit, date ranges, and age. Applying these filter conditions constrains the output to a certain population (cohort). The first view of our CD (Home) displays information for every single patient of the filtered population including end-, begin of surgery, vital signs, and the POD prediction risk. The second view (Statistics) provides demographics and additional incidence information across all patients of the filtered population. The last view (Metrics) provides insights into performance metrics, like area under the receiver operating characteristic curve (AUROC), regarding the filtered patients. We demonstrate a walk-through all these pages and apply different filter conditions showing how our display content changes adaptively.

After showing our CD design, we highlight strengths and limitations of our prototype. One the one hand, we can show how a translation of data science in clinical practice might look like. On the other hand, data delays, data inconsistencies, and technical challenges might hinder the user-acceptance of our CD prototype.

This work was conducted under ethics approval EA4/254/21 granted by the ethics committee at Charité – Universitätsmedizin Berlin.

4. Brief Curriculum Vitae

Niklas Giesa studied business information systems at the Hochschule Hannover in Germany between 2015 and 2020 focusing on data warehousing and data science. He wrote his mater thesis about the prediction of lethal intensive care cases in the context of the COVID-19 pandemic. Since 2021, he has been working as a PhD student at the Institute of Medical Informatics at Charité – Universitätsmedizin Berlin in Germany. Current research projects, funded by the German Academic Scholarship Foundation, investigate deep learning for the prediction of postoperative delirium.

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