Project Summary:

Acute respiratory distress syndrome (ARDS) is a severe form of acute hypoxemic respiratory failure affecting 10% of patients admitted to the intensive care unit (ICU) in the United States. In-hospital mortality of 35-46% has been reported across the spectrum of mild-severe ARDS, and one third of patients with initially mild ARDS will progress to moderate or severe ARDS. Over the last 20 years, multiple studies have reported improved outcomes for ARDS patients using specific ARDS targeted therapies. However, ARDS remains persistently under-recognized and challenging to diagnose. Only one third of ICU providers correctly identify ARDS on the first day when diagnostic criteria are met, and less than two thirds ever recognize the diagnosis in the ICU. This under recognition of ARDS may prevent some patients from receiving lifesaving therapies necessary for treating the disease. Attempts to automate ARDS diagnosis using rule-based algorithms have seen limited success, and require analysis of subjective data from patient histories, like chest scans, which limit diagnosis automation, timeliness, and study reproducibility.

To improve the current state of the art of ARDS detection technology, we intend to utilize objective and readily available data including both ventilator waveform data, (VWD) and electronic health record (EMR) data to 1) improve the recognition of ARDS, and 2) identify high-risk ARDS patients most likely to benefit from additional ARDS treatments. For this task, we will make use of an existing dataset of VWD from over 500 patients receiving mechanical ventilation, including 156 patients with confirmed ARDS. Our preliminary analyses using a machine learned model and a subset of lung physiology features derived solely from VWD, suggest that ARDS can be diagnosed in the absence of a chest scan or medical history. In Aim 1 of this proposal, we will improve our existing model used for discriminating ARDS by adding objective EMR data, and additional features extracted from VWD, such as patient respiratory compliance and airway resistance. Our next focus will be to predict worsening of ARDS severity in intubated patients based on Berlin criteria. So in Aim 2, we will evaluate the best tools for predicting increases in ARDS severity, and which types of temporal information yield the best predictive results.

We hypothesize that model development using additional objective data derived from VWD analysis and the EMR, along with advanced analytic techniques, will further improve ARDS diagnosis, and enable the prediction of clinical trajectories in patients with ARDS. The proposed work will yield innovative clinical decision support models that can be used to improve the state of the art in automated ARDS diagnosis. Our predictive modeling will also enable greater insight into the times when physicians can perform clinical interventions to arrest ARDS induced physiologic deterioration. Ultimately, these innovations could save lives by quickly detecting ARDS, and alerting physicians to begin or intensify ARDS focused therapies based on patient pathophysiologic state.