# Specific Aims

Acute respiratory failure (ARF) requiring mechanical ventilation is common in hospitalized patients; prolonged mechanical ventilation often leads to multi-organ failure. We will model electronic medical record (EMR) and pragmatic clinical trial data to predict and to prevent acute severe respiratory failure in hospitalized patients.

**Severe acute respiratory failure (ARF) requiring mechanical ventilation leads to increased mortality,** increased cognitive and functional impairment. EMR surveillance can identify hospitalized patients at risk, days before their deteriorating conditions are typically recognized; earlier initiation of preventive interventions can reduce morbidity, mortality and expenses: My mentor Dr. Gong is leading a two phase pragmatic clinical trial: APPROVE, phase 1, develops a classical algorithm to identify patients at risk; PROOFCheck, phase 2, aims to improve outcomes by triggering a prevention checklist targeting those patients the APPROVE algorithm identifies.

**Hierarchical modeling may be transformative for EMR-based prediction and prevention** and exploit the nested hierarchical granularity typical for EMRs. We propose to fit a more sophisticated hierarchical prediction algorithm than currently developed in APPROVE; we propose (a) to allow model parameters to vary between patients, medical floors, services or institutions and (b) to model temporal effects, e.g. seasonal effects, shifting population characteristics or heterogeneous provider behavior which might otherwise limit prediction accuracy. Incomplete clinical data limit prediction algorithms, but are characteristic for EMRs. I will develop new data impu- tation algorithms using auxiliary data, a novel approach to overcome issues with missing at random assumptions.

**Hierarchical models improve prediction over classical approaches owing to additional information** , gained from (a) modeling the rich spatial and temporal organization of EMRs more realistically, (b) imputing in- complete data from auxiliary data and (c) partial pooling. Patients treated by the same team, in similar settings will show similar clinical trajectories and responses. Partial pooling will improve precision and accuracy by informing parameter estimates with data from all other patients, using information from different but related subsets, espe- cially in subgroups with sparse data. The near real-time *integration* of auxiliary data imputation and hierarchical modeling with partial pooling into one coherent EMR-surveillance model is groundbreaking.

**Novel algorithms push the envelope of computability for Bayesian prediction models.** We choose Bayesian inference, novel for EMR prediction, for its flexibility in hierarchical modeling. Computational implemen- tation can be challenging. My co-mentor Dr. Gelman is leading the NSF-funded development of the probabilistic programming language Stan. His novel algorithm achieves much faster model convergence and parameter esti- mation. My second co-mentor Dr Hall is also a seasoned Bayesian statistician. He will supervise me for clever statistical formulation or transformation to further push the boundaries of computability for large EMRs. My ex- ceptional and multidisciplinary team of mentors is lead by Dr. Gong with her clinical angle on Big Data science. Together, we will integrate innovative approaches to data imputation with advanced hierarchical prediction models to form a near real-time EMR-based clinical decision tool with practical utility in critical care. The integration of pioneering statistical modeling with pragmatic clinical EMR-surveillance constitutes our unique innovation.

**Hypothesis:** *Compared to classical approaches, joint hierarchical Bayesian models improve prediction, prevention and compliance analysis in a pragmatic trial to prevent respiratory failure in hospitalized patients.*

### Specific aims

**Aim 1: To improve incomplete data imputation and early prediction of acute respiratory failure.**

*SA 1a:* To build a pragmatic EMR-based hierarchical Bayesian model implemented in the ultra-fast statistical software Stan to predict a composite outcome [death or prolonged mechanical ventilation > 48 hours] in inpatients. *SA 1b:* To further develop Bayesian data imputation algorithms of missing clinical data using auxiliary data, to identify auxiliary measure properties (ceiling, floor and threshold effects). To integrate imputation and prediction in one coherent hierarchical Bayesian model and to assess the predictive performance compared to the classical algorithm by Dr. Gong by the area under the curve (AUC) of their receiver operating characteristics (ROC).

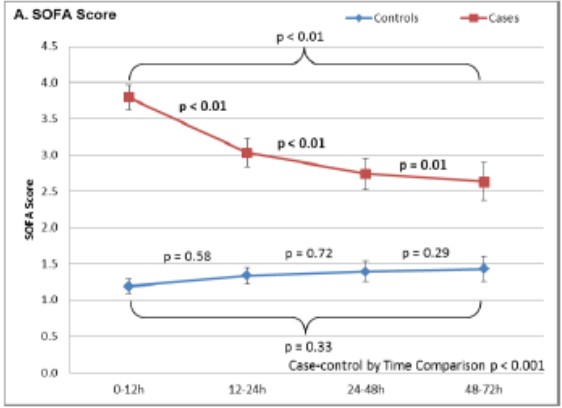
### Aim 2: To model temporality (institutional learning, seasons) and investigate provider compliance.

*SA 2a:* To investigate patient and provider characteristics as drivers of poor provider compliance in PROOFCheck, Dr. Gong’s pragmatic trial, to inform the ongoing PROOFCheck trial implementation and to focus our retraining. *SA 2b:* To update our model continuously with new incoming patients to reflect their changing risk profile and to model institutional learning and temporal effects like seasons and endemics.

# Research Plan

## Significance

**Respiratory failure in hospitalized patients can be predicted and should be prevented.**

Acute respiratory failure (ARF) requiring mechanical ventilation is com- mon in hospitalized patients, consuming a disproportionate amount of health care resources in the USA [2](#_bookmark15). Short term mechanical ventilation can be life saving, but prolonged mechanical ventilation often leads to multi-organ failure and death [2;3](#_bookmark16). Most research focuses on *established* respiratory failure in the ICU, while detectable clinical signs and symp- toms often herald the impending respiratory decompensation much ear- lier [4](#_bookmark17). Dr. Gong co-developed the LIPS score to identify patients at high risk for Adult Respiratory Distress Syndrome in the emergency depart- ment [5](#_bookmark18), which proved equally able to discriminate the 587 patients in the

cohort who progressed to severe ARF requiring > 48 hrs of mechanical ventilation. She also demonstrated that predictive scores deteriorate as early as 24-48 hours before ICU admission [Figure [1]](#_bookmark0) [1](#_bookmark14); but such omi- nous signs are either not recognized or not acted upon [6;7](#_bookmark20). Early inter- ventions and preventive measures(e.g antibiotic therapy, diuretics and

Figure 1: Deterioration of the Sequential Organ Failure Assessment score (SOFA) can be de- tected 24-48 hours before clinical deterioration leads to ICU admission; p-values reflect pair- wise comparisons between consecutive time intervals, adjusting for patient characteristics. [1](#_bookmark14).

head elevation) would be able to stop or reverse the clinical deterioration and/or prevent progression to multiple organ failure and prolonged mechanical ventilation or at least attenuate the subsequent clinical course [8;9;10;11](#_bookmark24).

Checklist intervention examples

**Prevent respiratory insufficiency** *Early goal directed therapy* [*12*](#_bookmark25) *Adequate early antibiotics* [*13*](#_bookmark26)**Decrease mechanical ventilation** *Daily sedation break* [*14*](#_bookmark27) *Spontaneous breathing trials* [*15*](#_bookmark28)

**Limit transfusion-related lung injury**

*Restrictive transfusion strategy* [*16*](#_bookmark29)

Table 1: Examples of checklist interven- tions, references documenting effect.

**A pragmatic clinical trial to predict and prevent mortality from res- piratory failure in hospitalized patients.** My mentor Dr. Gong is lead- ing a [NHLBI-funded](http://projectreporter.nih.gov/project_info_description.cfm?projectnumber=1UH2HL125119-01) multi-center cluster randomized pragmatic trial in two phases. (1) the first phase APPROVE aims to identify patients at risk by building classical logistic regression models based on electronic medical records (EMR) to Accurately Predict PROlonged Ventilation. (2) In the sec- ond phase PROOFCheck, identification of a patients at high risk triggers a decision support tool and bundled checklist interventions, proven to pre- vent organ failure in critically ill patients [12;13;14;15;16](#_bookmark29). CITE CLINICAL TRI- ALS.GOV. *Hypothesis:* Early implementation of a checklist of preventive measures [(1),](#_bookmark1) reduces severity of organ failure, mortality and duration of mechanical ventilation in in patients at high risk identified by APRROVE.

**Electronic medical records are an eminent example of richly structured and correlated Big Data.** Ex- emplified by Dr. Gong’s pragmatic trial, they hold enormous promise for outcomes research across a wide swath of clinical domains ranging from pediatrics to psychiatry, from maternal health to mortality from can- cer [17;18;19;20;21;22](#_bookmark35). However, large electronic medical data sets are not just bigger in that there are more instances of the same thing, (e.g. more patients would make data analysis only easier). Rather, there is more breadth to the data, and in the case of pragmatic trials, more heterogeneity, more subgroups, locations, or time granularity than is currently being modeled, more frequent and detailed measurements than can easily be incorporated into classical models. This currently limits the scientific hypotheses and clinical inferences, that can be explored and evaluated. In Dr. Gong’s trial in particular, we desire more fine-grained predictions to individualize prevention.

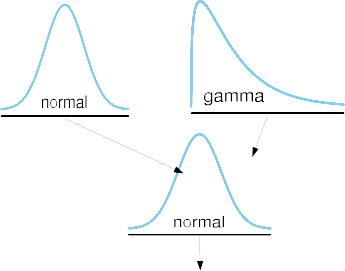
**We can individualize prevention by targeting patients at risk.** Preventive measure, for example goal tar- geted resuscitation, decrease respiratory failure requiring mechanical ventilation, when they are initiated early [10](#_bookmark23). However, an indiscriminate approach to prevention of respiratory failure in hospitalized patients will be ineffective, because only one in 30 hospitalized adults requires mechanical ventilation. Secondly, individualizing preven- tive and therapeutic measures specifically based on patient characteristics will be more efficient in preventing potentially irreversible end organ damage, while also leading to improved compliance by providers and cost ef- fectiveness. So how can we improve and individualize prediction and prevention?

## Hierarchical modeling is transformative for EMR-based prediction.

**Observations and outcomes in EMRs and pragmatic trials will be nested hierarchically.** For example, in APPROVE and PROOFCheck, repetitive oxygen saturation measurements will be similar in the same patients; the closer in time they are, the higher the correlation between repeated observations. Equally, patients seen by one and same hospitalist will tend to have similar outcomes, predicted by that physician’s behavior and qualities. As an example, some physicians (or services) will follow a more liberal fluid management, others will emphasize early diureses; clearly this choice will summarily affect the respiratory failure risk of specifically those patients under this physician’s care. Generally, physicians in large academic medical systems like ours are organized in services, which are integrated across wards, clustered in several hospitals. Consequently, the observations in our hospitalized patient cohort, their outcomes and their propensity to respond to treatments, all are hierarchically nested; this requires more than just fitting well-known models at larger scales.

**Hierarchical models better exploit the fine-grained multilevel structures of electronic medical records** and may therefore optimally predict acute respiratory failure leading to prolonged mechanical ventilation or death in our trial cohort. Fitting our predictive regression model, we would want the regression coefficients to vary by group (e.g. by service, by medical unit, by hospital), to realistically model the multifaceted correlations seen in actual clinical practice. The number of parameters to estimate grows very quickly and so do the potential interactions. Even with very large data sets, the sample size in each subgroup will shrink rapidly; estimates using least squares or maximum likelihood will become noisy and thus often become essentially useless. One solution lies in hierarchical modeling, where we estimate hyper-parameters and hyper-hyper-parameters (Figure [2),](#_bookmark2) to represent how lower level parameters vary across different groupings [23](#_bookmark36).

### Partial pooling is more efficient for prediction. Predic-



ρ

τ

α *,*β

*~*

*~*

μ

*~*

σ

tion based on "partial pooling" outperforms (a) the "No-pooling" and (b) the "Complete-pooling" approach, as can be shown mathematically or via cross-validation [24](#_bookmark37). Using (a) the "No- pooling" approach, we estimate the model for each specific subset of interest separately. But if we want to fully address and explore the complexity and granularity, the richness of the EMR data, this leads to far too many sub-classifications, thus too small samples in any given subgroup for useful inferences. Employing (b) "Complete pooling" or structural modeling consti- tutes the other extreme of the spectrum, but the implied hard constraints on the coefficients in different groups may lead to bias: we loose information, because we cannot learn from groups where we have more data. We choose the middle

*yi ~*

Patient Level

⏟logistic (β0 +∑*i* β*i xi* )

Service Level

*=*

*p*

*n*

Hospital Level

ground: Prediction using "partial pooling" or hierarchical mod- eling is especially effective for our richly organized EMR data, because the estimate of each individual parameter is simulta-

*yi*∼Binomial ( *p , n*) β*o*∼Normal (μ *,* σ) μ∼Normal (ρ *,* τ) σ∼inv-gamma (ν *,* κ)

Figure 2: Distrogram to illustrated the hierarchical struc-

ture of patient trajectories. Patient level regression co- efficient *β*0 varies across medical services, service level mean *µ* and within-service variance *σ* vary by hospital.

neously informed by data from all the other patients in our cohort, improving prediction in particular for subgroups with sparse data. [25](#_bookmark38).

*We hypothesize that hierarchical modeling may better identify hospitalized patients at risk for acute respiratory failure leading to prolonged mechanical ventilation or death than the APPROVE prediction algorithm.*

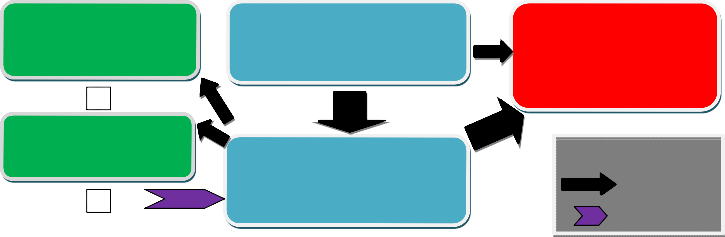
**Heterogeneous and incomplete clinical data may limit prediction and implementation.** Variables with strong predictive power in our model may not be recorded in all patients or may be missing for the time window needed for prediction, limiting development of the prediction algorithm, implementation of the therapeutic inter- ventions and the trial itself. Incomplete data are the hallmark of EMRs. In our data set we find for example that an arterial blood gas (ABG) to assess arterial oxygen tension is often unavailable for the prediction time window, because it was not requested by the physicians. To improve prediction for cases with incomplete data, we can impute the missing data using *multiple imputation*. Likelihood-based mixed effects models for incomplete data give valid estimates *if and only if* the data are ignorably missing; that is, the parameters for the missing data process are distinct from those of the main model for the outcome, and the data are missing at random (MAR) [26](#_bookmark39).

However, this is an unreasonable assumption for EMRs; in our example, physicians will request ABGs based on the patients respiratory co-morbidity and clinical hypoxia symptoms. Data will not be MAR. Instead, incomplete data will be associated with predictors and outcomes; this could lead to biased imputations.

**Auxiliary data can be used to impute incomplete medical records.** Auxiliary data are additional informa- tion available in the form of variables known to be correlated with the missing data of interest [27](#_bookmark40). If the physician did not request an ABG, instead peripheral oxygen saturation and or oxygen therapy may be available and could be used to impute the arterial blood oxygen tension [Figure [3].](#_bookmark3)

This approach avoids the perils associated with

missing at random (MAR) assumptions, when fit-



***Auxiliary variable 1***

Low peripheral oxygen saturation

Predictor 1

Beginning Pneumonia

+

Outcome

Severe respiratory failure leading to mechanical ventilation

***Auxiliary variable 2***

Oxygen Therapy

**Legend**:

=

Predictor 2

Arterial blood gas oxygen concentration decreases

[28](#_bookmark41)

ting a non-ignorable missingness model

. Adding

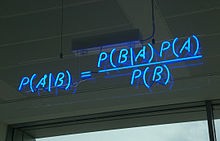
Figure 3: Incomplete data can hinder outcome prediction, but we can impute incomplete data from auxilliary information. For example, pneu- monia (causing to low oxygen tension), may cause respiratory failure. If arterial blood gas results are missing, we can impute the oxygen tension from oxygen therapy and/or peripheral oxygen saturation. [29](#_bookmark42).

Causation Imputation

auxiliary variables not included in the main model for multiple imputation, in other words using addi- tional information that is correlated with the missing outcome is an emerging approach to help correct bias [30;31;32](#_bookmark45), often relying on Bayesian methods for the multiple imputations approach [33;34](#_bookmark47); joint hierar- chical modeling, including the use of auxiliary data to impute incomplete patient records will improve the prediction model and facilitate smoother imple- mentation of the algorithm into the clinical trial [29](#_bookmark42).

*We hypothesize that joint hierarchical modeling, incorporating the use of auxiliary data to impute incomplete patient records, will improve our prediction model compared to classical prediction with multiple imputation.*

**Seasonal effects and institutional learning can bias risk prediction and can thwart implementation** or imperil the effectiveness of our efforts to mitigate the risks of severe respiratory failure in hospitalized patients.

The composition of our hospital population, their co-morbidities and risk profiles change over time, altering which patient characteristics best predict severe adverse respiratory failure and mechanical ventilation. More importantly, during the imple- mentation phase of previous preventive trials we noted that providers learn, changing their behavior as a result of trial participation. As trials progressed providers imple- mented previously underutilized interventions more frequently even before they were

prompted. We term this effect institutional learning. On the other hand, the transi-

tion of junior and senior providers through their training and to other institutions and new personnel joining the staff, may led to lessons learned being forgotten again. Last but not least, respiratory disease is affected by seasonal and secular effects;

Figure 4: Bayes Theorem: The

posterior probability *P* (*A|B*) is the prior probability *P* (*A*) up- dated with the likelihood *P* (*A*)

influenza prevalence for example is seasonal and characterized by major and minor epidemics. Seasons and epidemics will affect the predictive power of any model and hence also alter the risk profile of our patients over time. Institutional culture and individual provider behavior change in response to trials and quality improvements interventions; patient populations change over time. Respiratory patients are plagued by seasonal deterioration. These temporal, seasonal and secular effects will alter the predictors of risk in our model and affect its implemen- tation. We will therefore include institutional learning, seasonal effects and continuously update our model with new patient data to account for said changes in the risk profile. The integration EMR-triggered prediction and prevention with institutional learning, secular and seasonal effects as well as data imputations from auxiliary data within one coherent (Bayesian) model is certainly novel, but how can it be implemented in one coherent model?

## Innovation

**Bayesian hierarchical modeling is groundbreaking in EMR-based prediction,** and particularly suited for joint hierarchical modeling. With their inherent flexibility and robustness [35;36](#_bookmark49), Bayesian hierarchical models may outperform classical models for EMR-based prediction owing to the integration of additional information through "partial pooling" [37](#_bookmark50) and the imputation of incomplete records from auxiliary data. After computers and Markov Chain

Monte Carlo algorithms became widely available in the 1990s, applied Bayesian work expanded into [39;40](#_bookmark53) more recently EMR-based prediction [41;42;43](#_bookmark56) and Big Data [44](#_bookmark57). *However, there are no Bayesian hierarchical prediction model based on large EMRs.*

**A brief introduction to Bayesian inference and its computational implementation.** According to Bayes’ Theorem, shown in Figure [4,](#_bookmark4) prior information *P* (*A*) is combined with new data *P* (*B*), (known as the likelihood) to yield an *updated* estimate for the probability of a hypothesis *P* (*A*) given the data *P* (*B*), called the posterior dis-

tribution *P* (*A|B*) [45](#_bookmark58). The Bayesian approach is analogous to clinical decision-making [40](#_bookmark53). Physicians continuously

update their preliminary diagnosis as new information comes in. Prior belief *P* (*A*) in a diagnosis may be weak- ened by new laboratory information *P* (*B*), leading to an updated diagnosis given the lab data *P* (*A|B*) [46](#_bookmark59). Bayesian

inference for multi-layered (hierarchical) models can often not be derived analytically; instead we calculate nu- merical approximations of the multi-dimensional integrals to obtain the posterior distributions of the parameters of interest. In technical terms, Markov Chain Monte Carlo (MCMC) based Bayesian inference methods sample from a posterior probability distribution after building a Markov chain. MCMC simulation replaces intractable analytical integration with empirical summaries of samples from the posterior distribution [47](#_bookmark60): *Instead of analyzing the odds, we simulate throwing the dice repeatedly.* But MCMC simulations can be slow to converge for large EMRs.

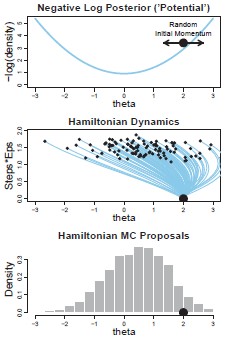
**Pushing the envelope of Bayesian inference for EMR-based pre- diction**, we will implement the Bayesian model in parallel in the ultra-fast probabilistic programming language software Stan developed by my co- mentor Dr. Gelman [48](#_bookmark61). Stan’s Hamiltonian Monte Carlo algorithms [48](#_bookmark61) and clever statistical formulation push the boundaries of computability [24](#_bookmark37). For example non-centered parameterization allows sampling in the standardized normal space, enhancing the effective sample size in Stan taking full advantage of the faster convergence to overcome computational limitations of Bayesian hierarchical models for very large EMR data sets [24](#_bookmark37). Stan is based on Hamiltonian Monte Carlo (HMC) [24](#_bookmark37), a Marcov chain Monte Carlo (MCMC) algorithm, which avoids the sensitivity to correlated parameters that plague many MCMC methods by introducing auxiliary momentum variables [50](#_bookmark63) as illustrated in Figure [5.](#_bookmark5) HMC is dependent on tuning the reciprocal relationship of the crucial parameters step size and desired number of steps. If the lat-

Figure 5: Hamiltonian MCMC uses momen-

tum to optimize the next proposal. The higher momentum of the current position (black dot) is indicated in the top panel. The middle panel illustrates how random samples are drawn to the mode of the posterior distribution (lower panel) leading to faster convergence and higher effective sample size. Fig 14.1 in Kruschke [45](#_bookmark58).

ter is too large, efficiency is low, or too small, we can see undesirable random walk behavior. To overcome this, Dr. Gelman’s team developed and implemented the No-U-Turn Sampler (NUTS), a recursive algorithm to automate and optimize tuning the HMC [50](#_bookmark63).

**Analyzing and advancing implementation is decisive** for out- come improvement and research. Imperfect fidelity (poor provider com- pliance) is a major concern also in our PROOFCheck trial, just as non- compliance is a major obstacle to the effective delivery of health care

and improved outcomes in general [51](#_bookmark64). The targeted interventions triggered by our EMR-prediction algorithm will

only prevent respiratory failure if our physicians and nurses actually implement them. Improving fidelity of health care providers with evidence based interventions continues to be a challenge and is under-researched [52](#_bookmark65) and little is known on how to reproduce multi-faceted interventions (specially directed toward providers) to improve clinical outcomes [53](#_bookmark66). As long as we do not understand what drives provider fidelity and patient compliance with the preventive measures proposed to our providers for their high risk patients [54](#_bookmark67), we ignore the best means to

translate widely accepted interventions and new findings of outcomes research into practice [55](#_bookmark68). We need to understand better what patient and/or provider characteristics hinder compliance with the triggered preventive checklist interventions to ensure care is in accordance with accepted evidence based best practices.

**We use a pragmatic trial to investigate provider fidelity.** Pragmatic trials like Dr. Gong’s may result in valid more estimates of effectiveness for more realistic health care scenarios [56;57](#_bookmark70); we will use her pragmatic trial data to investigate incomplete fidelity, heterogeneity and difficulty in clinical implementation. An example with problematic fidelity relevant for PROOFCheck is blood product management where implementation of rational transfusion blood product management is still sketchy and very heterogeneous across the nation [61](#_bookmark74). Weiss et al. demonstrated that direct prompting for best practices improves provider compliance in the ICU and outcomes such as duration of mechanical ventilation or length of stay [62](#_bookmark75). We hypothesize that fidelity will be associated with certain provider and patient characteristics; their investigation will allow more focused re-education efforts and adaptation of the checklist implementation.

## Summary of the impact

Acute respiratory failure in hospitalized patients leading to prolonged mechanical ventilation with the inherent mortality and morbidity constitutes a serious health care challenge. We will tackle this by combining innovative approaches to data imputation with sophisticated hierarchical prediction models to form a near real-time EMR- based clinical decision tool with practical utility in critical care. We use the opportunity to investigate poor provider fidelity, a serious and under-researched barrier to outcomes research in the implementation of evidenced-based care. Our findings will have implications beyond our trial for any clinical research, indeed for the implementation of evidence-based-medicine at large. Changes in reimbursement give providers a stake in patient outcomes and led to a keen interest in the prediction and prevention of adverse event in hospitalized patients. This project advances hierarchical Bayesian models to implement this paradigm shift in very large EMRs, triggering personalized interventions that deliver outcome improvements. This is novel and has not been attempted to our knowledge. But our impact goes beyond improving morbidity and mortality from respiratory disease in hospitalized patients through improved prediction and prevention, beyond investigating drivers of poor provider compliance. We will develop new methods to impute incomplete electronic medical records from auxiliary data and pioneer Bayesian hierarchical prediction models for large EMR data. Our proposal is unique and novel in its integration of cutting edge methods from clinical, statistical and computer science to fully realize the promise of Big Data in perioperative medicine.

## Approach

My research project will be closely aligned with my mentor’s NIH-funded pragmatic two phase trial. Aim 1 will utilize the processed data of APPROVE to improve the prediction model and Aim 2 will use the data from the implementation of PROOFCheck to investigate fidelity of the providers with the EMR-triggered interventions.

**Aim 1: To improve incomplete data imputation and early prediction of acute respiratory failure.** *Hypothesis: The integration of auxiliary data imputation and multi-level Bayesian modeling will improve prediction of severe respiratory failure in hospitalized patients compared to classical statistical approaches.*

**For specific aim 1a,** we will build a pragmatic EMR-based hierarchical Bayesian model to predict a composite outcome [mechanical ventilation prolonged beyond 48 hours or death] in hospitalized adult and compare our Bayesian approach with the existing frequentist algorithm used by Dr. Gong in her pragmatic trial.

**Population:** We will include all adults patients, admitted to the Montefiore Medical Center during the study period, excluding only those who are chronically ventilated at home or who have Do not resuscitate orders at the time of hospital admission (Table 1: Inpatient population at Montefiore Medical Center.) As part of APPROVE, the pragmatic trial by Dr. Gong described in detail under Significance, EMR data abstraction for all adult admissions in 2013 at Montefiore Medical Center and Mayo Clinic Rochester ; we will build our Bayesian hierarchical model based solely on Montefiore patients. We will divide the cohort into separate fitting and validation sets.

**Predictors:** Many independent variables are candidates for potential inclusion into our Bayesian hierarchical model. We will consider these and additional time-invariant and time-variant demographic and clinical data. Examples for demographics are gender, age, medical service or ward, examples for physiological and clinical predictors are heart rate, blood pressure or lab tests, respectively. Certain predictors will require summary aggregations and (logarithmic) transformations to induce variance stability.

**Outcomes:** Our primary dichotomous outcome will be acute respiratory failure requiring mechanical ventila- tion longer than 48 hours. Outcomes are specified as positive for (a) mechanical ventilation lasting longer than 48 hours or (b) mechanical ventilation lasts less than 48 hours, but the patient died within 96 hours of the calculated score. Patients that are not on prolonged ventilation within 96 hours or discharged alive from the hospital will be considered negative.

**Bayesian hierarchical modeling to reflect the nested structure of health care.** We will build a Bayesian hierarchical multivariate logistic regression model of time-invariant and time-variant demographic, clinical and administrative variables. Our Bayesian hierarchical modeling will represent the multi-level nested structure of current health care, with levels for medical or surgical service the patient is under, the floor or ward where the patient is cared for, the institution the patient is admitted to. We will also consider other random effects for example for co-morbidity and other time-invariant patient specific descriptors. We illustrate this nested structure in a simple logistic model with hierarchical levels for patient, service and hospital.

**Patient level** [**(1)**](#_bookmark6)On the left, we model at the pa-

*Y ∼ Binom*(*α, n*); *α* = *inv*\_*log*(*β*0 + *β*1 *∗ PaO*2) (1)

tient level, the probability *alpha* that a patient will de- velop the dichotomous event *Y* , acute respiratory fail-

ure requiring mechanical ventilation, using arterial oxygen tension *PaO*2 as a predictor in a simple logistic regres- sion model. However, patients are typically assigned to hospital services. Pulmonary service patients may have a lower baseline *PaO*2, while surgical patients tend to have normal lung function.

**Service level** [**(2)**](#_bookmark7)On the left we develop our hier-

*β*0 *∼ Normal*(*γ*0*, τβ*0 ); *β*1 *∼ Normal*(*γ*1*, τβ*1 ) (2)

archical model to allow different intercepts *β*0 repre-

senting the average *PaO*2 of patients in the various medical and surgical services estimating different service level mean intercepts *γ*0. Under a medical service, smaller changes in *PaO*2 may be indicative of respiratory deterioration compared to a surgical service, where larger drop in arterial oxygen tension predicts outcome. We may allow the regression coefficient for the slope *β*1 to vary around different mean slopes *γ*1 at the service level.

**Hospital level** [**(3)**](#_bookmark8)Some hospitals may cater to an economically disadvantages population, which is

*γ*0 *∼ Normal*(*δtau*0 *, ζ*); *τβ*1 *∼ Normal*(*δtau*1 *, κ*) (3)

sicker on average. To reflect this, we may model the

mean intercept *γ*0 for the services hierarchically at the hospital level. Patients differ very much between services in some hospitals, while others may have a more homogeneous patient distribution; we can model this *variation τβ*1 of the mean slope *γ*1 within services at a given hospital to capture the variability of *PaO*2’s predictive effect.

**In APPROVE, the compared frequentist prediction model will be build by Dr. Gong’s statistical team** to identify hospitalized patients at risk for prolonged mechanical ventilation and death. The score at the selected start time will be used to determine the best cutoff score to identify the patients with the highest risk of developing prolonged mechanical ventilation.

**Data Acquisition** Data will be abstracted from a clinical data warehouse(see Environment and Resources). A multi-prong approach for capturing complete, longitudinal data in real-time, near real-time, or asynchronously from the EMR replica will be used. Secured electronic data capture tools provided by the Montefiore Enterprise Clinical Research Management System will be used to streamline, quality control, normalize, and manage data collection and data entry efforts. A fully de-identified, study specific database of all study variables will be compiled for model development and validation. When subsequently patient data from additional regional medical centers are incorporated.

**Model checking** We will look at auto-correlation, trace-plots and calculate the Gelman and Rubin’s MCMC Convergence Diagnostic *R*ˆ to evaluate the the convergence of our Markov chain Monte Carlo (MCMC) simu- lations using [shinyStan,](http://andrewgelman.com/2015/03/02/introducing-shinystan/) the interactive visual application to graphically explore hierarchical models, we devel- oped [65](#_bookmark78). Others reviewed shinyStan’s installation and utility on [YouTube.](https://www.youtube.com/watch?v=X31xqNHcvQs) In evaluating our Bayesian model’s predictive performance, exploratory graphical [66](#_bookmark79) and confirmatory formal posterior predictive assessment us- ing discrepancies [67](#_bookmark80) will complement each other to compare the patient test set to simulated replications from our fitted hierarchical Bayesian model. As a simple example, for each draw of the estimated parameter *θ*

from the posterior *p*(*θ|y*) we simulate data *yrep* from the posterior predictive distribution *p*(*yrep|y*). Using the

simulations of *yrep* we can make various graphical displays comparing our observed data to the replications:

If our model is a good fit, then data generated by the model using the

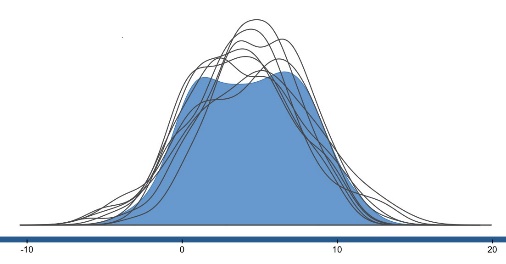
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*p*(*yrep|y*) =

*p*(*yrep|θ*)*p*(*θ|y*) d*θ* (4)

estimated parameters should have a distribution similar to the original data we observed. We illustrate this idea behind posterior predictive checking [68](#_bookmark81) in Figure [6,](#_bookmark9) generated in our software package shinyStan [65](#_bookmark78):

As a more sophisticated approach we will graphically contrast the vector test statistics *T* (*y*) versus replicated data *T* (*yrep*) to detect a potential misfit of model to data [66;69](#_bookmark82) Analogously, we will use predictive validation to adjust for overfitting of our model and perform a sensitivity analysis of our priors on key model parameteters [24;68](#_bookmark81).

**Model comparison** We will assess the plausibility of our posited hierar- chical model and its assumptions [68;67](#_bookmark80) and will compare it to the alternative classical model by Dr. Gong (based on a non-nested much simpler model [5](#_bookmark18)). As a simple approach, we will perform a nonparametric comparison of ar- eas under the curve (AUC) of the correlated receiver operating characteris- tics (ROC) curves [70](#_bookmark83) to assess their respective predictive performance [71;43](#_bookmark56), in other words to investigate if the hierarchical modeling improves prediction

of acute severe respiratory failure over the simpler classical model used by Dr. Gong. We will compare the models based on a different test set from the same population, to avoid biasing the comparison in favor of our more com- plicated, (possibly overfitted) hierarchical model. Cross-validation is widely used to compare statistical models for estimating out-of-sample prediction

Figure 6: Exploratory posterior predictive

checking using our software shinyStan [65](#_bookmark78): Visual comparison of the distribution of observed data (shaded in blue) to the distributions of the data simulated (thin lines) suggest a reasonable model fit.

error [72](#_bookmark85). However, in our case, we operate on the limits of computability and repeatedly fitting our Bayesian hi-

erarchical model to leave-one-out samples, could be computationally too expensive [73](#_bookmark86). Besides, for multi-level data, leaving partitioning the data for cross-validation should probably consider the hierarchical structure itself; indeed, cross-validation may not always be a sensitive instrument for model comparison [74](#_bookmark87). We will also explore the predictive information of our hierarchical model using posterior predicitve simulations and realized discrepan- cies [73;68;67](#_bookmark80). In parallel sampling [75](#_bookmark88), we will compare our Bayesian Model to the classical simpler algorithms using the minimum *χ*2 discrepancy, essentially equivalent to the classical goodness-of-fit test statistic [67](#_bookmark80). For additional validation, we will train our model with patient data from other participating institutions (Mayo Clinic Rochester and Florida) and test if our model outperforms the classical prediction models even in other ecological settings (say Mayo Clinic Rochester) or if the classical model is based on data from all institutions.

**Technical approach** Boolean combinations of data matching and natural language processing of the predic- tion algorithms will be used to scan a real time copy of the hospital’s clinical and administrative data including demographic, monitoring, pharmacy, laboratory, and physician notes for risk factors and physiological abnormal- ity. The rule engine (implemented in Java) will send out the alert to providers.

**For specific aim 1b,** we develop new Bayesian data imputation algorithms for missing clinical data using auxiliary data and we identify auxiliary measure properties (ceiling, floor and threshold effects). Missing data are a characteristic limitation of large electronic medical records and may bias our prediction model [17](#_bookmark30). Electronically medical records measurements not updated 24 hours earlier than the selected start time will be considered missing; as an illustrative example, we formulated a simplistic model illustrated in [Figure [3].](#_bookmark3) We combine the prediction of the dichotomous compound outcome *Y* , (defined as acute respiratory failure leading to mechanical ventilation and death) using latent arterial oxygen tension Ω in a logistic regression model in Equation [5](#_bookmark10) and [6:](#_bookmark11)

*Y ∼ Binom*(*µ, n*) (5)

We may have the *PaO*2

from an arterial blood gas (ABG) or not. Nota

*µ* = *inv*\_*log*(*β*0 + *β*1 *∗* Ω) (6)

bene, ABGs will certainly not be missing at random, but contingent on the

*PaO*2 value and respiratory outcome *Y* . If the *PaO*2 from the ABG is ob-

served, we will use it to predict the outcome *Y* . If no ABG was obtained, we impute the latent oxygen tension Ω

with a regression model from the auxiliary data *O*2 Saturation and *O*2 therapy:

Ω = *I*(*observed* = *true*) *∗ PaO*2 + *I*(*observed* = *false*) *∗ δ* (7)

*δ ∼ Normal*(*θ, τ* ); *θ* = *γ*0 + *γ*1 *∗ O*2*Sat* + *γ*2 *∗ O*2*Therapy* (8)

Our imputation approach exploits the

temporal relationship between variables in the longitudinal electronic medical

records [19](#_bookmark32). We will identify the auxiliary measure properties, ceiling and floor and potential threshold effects

effects, test the imputations against manually verified data and published algorithms and compare them to the simple and multiple imputation strategies planned for Dr. Gong’s pragmatic trial [76;77](#_bookmark90). We will perform posterior cross validation checks to investigate the appropriateness of our assumptions and incomplete data model [78](#_bookmark91).

### Aim 2: To model temporality (institutional learning, seasons) and investigate provider compliance.

To focus education efforts and improve implementation of preventive or therapeutic measures, we will investigate predictors of provider behavior. To most closely reflect the realistic situation of actual academic and community medical delivery settings, we need to take temporal and seasonal changes into account.

**For specific Aim 2a,** we will investigate provider compliance with the individual components of the checklist. During the second phase (PROOFCheck) of Dr. Gong’s pragmatic trial, providers of a patient identified as high risk by the frequentist prediction algorithm will be prompted electronically to implement concrete preventive and corrective measures from a list of widely accepted interventions. During roll-out, providers receive targeted education on prevention and best practice. During PROOFCheck, an interactive notification algorithm will suggest to the physicians patient specific interventions from the checklist to the clinicians via an electronic clinical interface. **Prediction of adverse events is useful only if followed by effective preventive action.** We will use data from PROOFCheck, the second phase of Dr. Gong’s pragmatic trial to analyze provider compliance (fidelity) with the proposed interventions. We will investigate which provider and patient characteristics predict compliance with which components of the intervention checklist to identify drivers of poor provider fidelity. Results will inform our compliance retraining for PROOFCheck in which I will actively participate during my second year.

**Population:** Hospitalized adults identified by the APPROVE algorithm as high risk

and intubated patients will be included in Dr. Gong’s PROOFCheck. PROOFCheck will limit recruitment to wards found to have higher prevalence of severe adverse respiratory events during the first phase of Dr. Gong’s trial (APPROVE). Patients chronically ventilated at home or who have DNR, will be excluded. I will include all data from all participating centers. We anticipate 12,000 patients enrolled into the trial over 4 years with estimated 60% coming from Montefiore. Hospital beds and annual numbers of ventilated patients for each hospital are presented in Table [2.](#_bookmark12)

**Outcomes,exposures and predictors:** My primary outcome will be provider compliance, a dichotomous event, defined as positive if the provider ordered the prompted preventive intervention. In order to measure and demonstrate compli- ance with the checklist, near real time (same day) transaction logs evidence for

Hospital Beds Venta

|  |  |  |
| --- | --- | --- |
| Montefiore | 620 | 815 |
| Weiler | 396 | xx |
| Wakefield | 369 | xx |
| Mayo Clinic | xxx | 440 |
| Mayo Florida | 646 | 230 |
| *Total* | xxx | xx |

Table 2: PROOFCheck hospital population (apatients ventilated)

compliance will be recorded electronically. We will consider time-invariant and time-variant provider and patient demographic and clinical data. Two hypothetical examples of provider and patient demographics as predictors fidelity: (1) junior residents may be less comfortable with stricter blood transfusion triggers compared to seasoned physician assistants; (2) providers fidelity with evidence based treatment recommendations may be contingent on patient gender, say for heart failure [79](#_bookmark92), likely an important predictor of respiratory failure in APPROVE. Time- variant patient characteristics (e.g. lab values) could determine provider fidelity; for example borderline blood hemoglobin concentration may influence compliance with PROOFCheck blood transfusion recommendations.

**Study design and model building** This is a prospective observational cohort study to investigate sustained provider fidelity with EMR-triggered preventive interventions in PROOFCheck, Dr. Gong’s pragmatic multicenter trial. We will build a Bayesian hierarchical multivariate logistic regression model of time-invariant and time-variant demographic, clinical and administrative variables, with levels for service, ward and institution, analogously to aim 1; the hierarchical structure is to reflect certain biases and attitudes ingrained in certain medical or surgical specialties or hospital wards, which may lead to different associations between provider and patient characteristics and provider fidelity with treatment prompts, for example service-specific reluctance to use triggers to minimize blood cell transfusion [80](#_bookmark93).

**For specific Aim 2b,** to reflect changing risk profiles over time, we will adjust our Bayesian model to update continuously with new incoming patients and adapt our model to include temporal effects, like institutional learn- ing, seasonal or endemic phenomena. Seasonal changes could for example be modeled by adding another level above the hospital level modeled in Equation [3](#_bookmark8) to our patient-service-hospital hierarchy illustrated in Figure [2:](#_bookmark2)

Equation [9](#_bookmark13) would thus allow the hospital level mean to vary over time to reflect

increases in the severity and prevalence of chronic obstructive pulmonary disease in the winter or to smooth over differences in annual flu prevalence.

### Limitations and feasibility of our research plan

*δtau*0 *∼ Normal*(*φ, ψ*) (9)

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| Pre K-award period | | 2016  K01 starts | Q1 | Q2 | | Q3 | Q4 | | 2017 | Q1 | | | Q2 | | Q2 | | Q4 | 2018 | Q1 | | Q2 | Q3 | | Q4 |
| IRB approval, extract and select variables, implement e-triggers | | Aims 1a and 1b  | | | | | | Aim 1 | | | Aims 2a | | | | | Aim 2b | | | | | |
| Joint (incomplete data and prediction) model | | | | | | Investigate provider compliance to inform training | | | | | | | | Integrate temporal effects like seasons and provider learning | | | | | |
| APPROVE | | U1 | PROOFCheck | | | | | | | PROOFCheck | | | | | | | | PROOFCheck -- | | | | | | |
| Fit | Validate | Train | | Randomize | | | 1 | 2 | | 3 | 4 | | 5 | | 6 | Compliance | | | RCT completed | | | Follow up | |

a

**Timeline**, detailing quarterly progress through the K01 training period: My research plan is well aligned with APRROVE and PROOFCheck, my mentor’s trial. Time consuming preliminary work (IRB approval, computerized data collection and cleaning, aggre- gation and standardization, identification of important predictors of respiratory failure) is already well under way. Cluster randomization [for hospital 1-6] begins soon after my K01 starts. Aim 1 will have considerable overlap into the second year, when concurrent fidelity analysis will inform compliance retraining for PROOFCheck. Rich data will sustain my final integration of temporal effects in the model.

Successful execution of my broad research plan is facilitated by its integration in APPROVE and PROOFCheck, my mentor’s ongoing trial, as illustrated in the Timeline above. The computability of our Bayesian model hinges on its effective computational implementation. My co-mentor, Dr. Gelman is personally invested in the realization of cutting-edge Bayesian models through our allied R01 research project. Several standalone components of my research proposal will lead to high impact publications; developing new missing data imputation using auxiliary data is novel, as is the analysis and improvement of poor provider compliance.

**My research is well aligned with NIH funding opportunities, institutional priorities and emerging paradigms** Together with my mentors Drs. Gong, Gelman and Hall, we are working on an aligned R01 application to the BD2K initiative in response to FAO PA-14-156 to further develop Bayesian computational algorithms for the soft- ware Stan, using Dr. Gong’s trial as use case. This K01 training and the PhD will give me the competitive edge to lead similar multi-disciplinary NIH applications as early stage principle investigator. Entering the field of Bayesian EMR-based prediction at its dawn with such a rigorous training will give me the opportunity to establish myself as a leading investigator and makes me a desirable collaborator and key player in my institution. I am particu- larly interested to extend our Bayesian tools to the "Perioperative Surgical Home" [82](#_bookmark95), where I published before [81](#_bookmark94) incorporating record matching across our regional academic databases [83](#_bookmark96).

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