Award Number: W81XWH-13-1-0056

TITLE: PREDICT: Pattern Representation and Evaluation of Data through Integration, Correlation, and Transformation

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REPORT DATE: February 2015

TYPE OF REPORT: Annual

PREPARED FOR: U.S. Army Medical Research and Materiel Command
Fort Detrick, Maryland 21702-5012

# REPORT DOCUMENTATION PAGE

*Form Approved*
*OMB No. 0704-0188*



| 1. REPORT DATE | 2. REPORT TYPE | 3. DATES COVERED |
|---|---|---|
| February 2015 | Annual | 1 Feb 2014 – 31 Jan 2015 |

**4. TITLE AND SUBTITLE**
PREDICT: Pattern Representation and Evaluation of Data through Integration,

Correlation, and Transformation

**5a. CONTRACT NUMBER**

**5b. GRANT NUMBER**
W81XWH-13-1-0056

**5c. PROGRAM ELEMENT NUMBER**

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**5d. PROJECT NUMBER**

**5e. TASK NUMBER**

**5f. WORK UNIT NUMBER**

**7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)**

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630 West 168th Street, Box 49
New York, NY10032-3702

**8. PERFORMING ORGANIZATION REPORT NUMBER**

**9. SPONSORING / MONITORING AGENCY NAME(S) AND ADDRESS(ES)**
U.S. Army Medical Research and Materiel Command
Fort Detrick, Maryland 21702-5012

**10. SPONSOR/MONITOR'S ACRONYM(S)**

**11. SPONSOR/MONITOR'S REPORT NUMBER(S)**

**12. DISTRIBUTION / AVAILABILITY STATEMENT**
Approved for Public Release; Distribution Unlimited

**13. SUPPLEMENTARY NOTES**

**14. ABSTRACT** The objective is to demonstrate that interactive data visualizations designed to transform and consolidate complex multimodal physiological data into integrated interactive displays will reduce clinician cognitive load and will result in reductions in medical error and improvements in patient care, safety, and efficiency. Research accomplishments include: 1) Devised methods to both filter and interpolate physiological data, 2) Created physiologic indices for clinically meaningful variation among several parameters using a version of empirical orthogonal functions, 3) Applied the above physiologic indices to create a patient overview visualization to help clinicians identify patients that are changing and inserted these indices into the sepsis specific decision support visualization, 4) Created a sepsis identification visualization tool to help clinicians identify patients headed for septic shock, and 5) Generated a visualization tool to help clinicians assess intracranial pressure and generate patient specific physiologic set-points for goal directed therapy, and 6) Demonstrate a real-time data feed to a visualization tool that contains elements from each of the three prototype visualizations. In the next period a cognitive experiment will be conducted to determine the effectiveness of these visualization tools.

**15. SUBJECT TERMS**

| 16. SECURITY CLASSIFICATION OF: | | | 17. LIMITATION OF ABSTRACT | 18. NUMBER OF PAGES | 19a. NAME OF RESPONSIBLE PERSON |
|---|---|---|---|---|---|
| a. REPORT | b. ABSTRACT | c. THIS PAGE | | | 19b. TELEPHONE NUMBER *(include area code)* |
| U | U | U | UU | 32 | USAMRMC |

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# INTRODUCTION

Intensive care unit clinicians may be confronted by more than 200 variables for critically-ill patients during rounds each morning.[1] In contrast people are not able to judge the degree of relatedness between more than two variables without assistance.[2] A late-2009 report by the National Research Council (NRC) suggests that information technology (IT) solutions for medicine should shift their focus from current solutions that provide cognitive support on each individual piece of equipment or report to one that supports clinicians in synthesizing massive amounts of data to acquire a conceptual model of the whole patient. [3] The hypothesis of this research effort is to demonstrate that reducing clinician cognitive load by consolidating complex multimodal physiological information into coherent images using data visualization will result in reductions in medical error and improvements in patient care, safety, and efficiency. Our research objective is to design, develop, and test a prototype data visualization system that integrates and presents complex disparate data streams into dynamic visualizations that enable clinicians to more easily assimilate the information and derive insight from it resulting in faster more accurate treatment decisions. There are 4 phases to this research. Phase 1 is to develop a paper prototype interactive visualization. In Phase 2 and 3 Columbia University investigators focus on data acquisition and analysis of data to construct patient cases for the purpose of the visualization experiments while Draper Laboratory investigators focus on developing the visualization tools detailed in Phase 1. During Phase 4 a set of experiments will be conducted to evaluate the effectiveness of the visualization against an unaided standard-of-care condition.

# BODY

The Statement of Work on this project is for Columbia University and Draper Laboratory Investigators to develop novel visualization tools that represent health data acquired from patients in the neurological intensive care unit of Columbia University Medical Center. The general aim of this effort is to demonstrate that interactive data visualizations designed to transform and consolidate complex multimodal physiological data into integrated interactive displays will reduce clinician cognitive load and will result in reductions in medical error and improvements in patient care, safety, and efficiency. Three case scenarios to focus on were identified in the scope of work. The first focus area is to develop a visualization to help clinicians identify patients that are changing physiological states and therefore require medical attention. We proposed applying empirical orthogonal function (EOF) analysis to identify patient states and variables that have changed over a specified time period. Once the clinician is alerted to a change in patient state, decision support tools should facilitate their clinical investigation and in making a specific decision that fall into one of three general categories: 1) identify a physiologic end point to guide goal-directed therapy, and determine the relative effectiveness of a specific or set of interventions in achieving those goals, 2) determine the onset of a secondary complication and intervene, 3) identify active physiologic processes that can affect overall clinical management. The project is broken down into four key deliverable milestones including: 1) prototype visualization development, 2) data collection, analysis, and deployment to back-end data system, 3) interactive visual interface complete and connected with the data, and 4) conduct cognitive experiments to evaluate the effectiveness of the visualization tools against an unaided condition.

Draper Laboratory human-factor engineers gained a comprehensive understanding of the needs and data requirements for the three case scenarios by completing (3/15/13) a cognitive work analysis (CWA) with clinical staff from the Columbia University Neurological Intensive Care Unit. Columbia University Investigators and Draper Laboratory human-factor engineers underwent an iterative process to translate the CWA results into requirements for prototype visualizations. Mockup visualizations were developed for an integrated system-level overview that utilizes empirical orthogonal functions (complete 4/26/2013), and for specific decisions related to patient development of sepsis (complete 4/15/2013) and intracranial pressure management (complete 4/26/2013). We deployed a back-end MongoDB database and have been able to deposit data into it. However, we found that building an interface to connecting the visualization tool directly to this data source was not realistic given the time constraints and need for experimenter control in the experiment. Instead we created static data files that are read directly for the purpose of the experiment. As we stated in our quarter report this has not impacted achieving the primary goals of the project. Alternatively however we have been able to incorporate elements of our visualization tools into a web-based visualization tool to connect to a real-time data stream (Milestone 2) as will be detailed later in this report. The results of the cognitive work analysis (reportable outcome 1) and prototype mockups (reportable outcome 2) are detailed below. Each mockup underwent a series of design iterations to ensure that the visualizations made sense for the tasks and decisions that the clinicians need to solve.

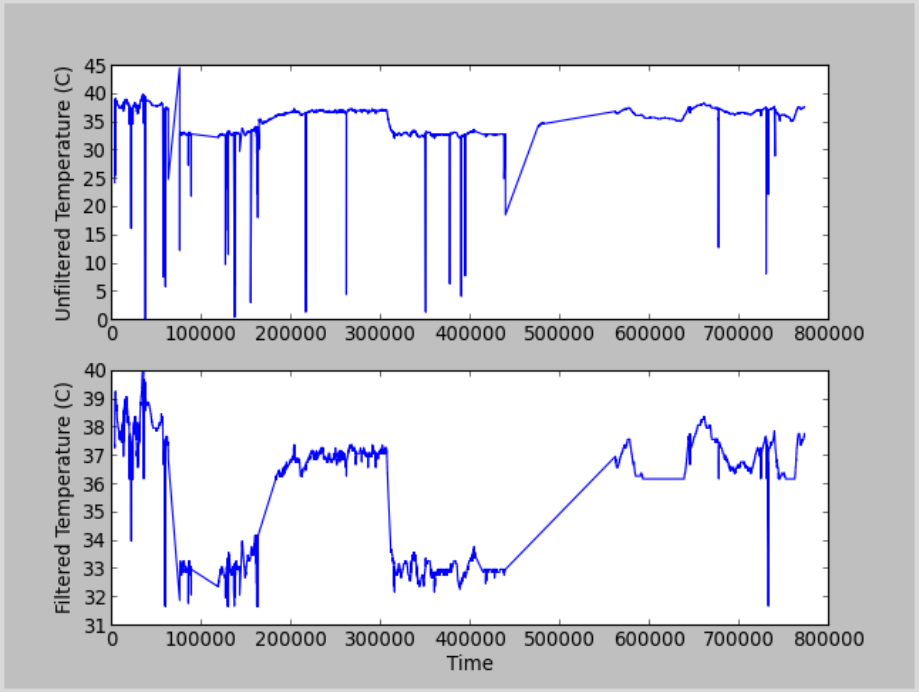
## *PATIENT OVERVIEW VISUALIZATION*

The goal of the patient overview visualization is to identify patient state changes and identifying patients that need clinician attention. The most difficult task for clinicians is not determining which patients are doing poorly – this is usually self-evident – it is determining which patients are *changing* and require intervention. We hypothesize that an interactive visualization can be designed to support clinicians in more quickly recognizing changes to patient state, situation awareness, and faster ability to pinpoint emerging situations. Empirical orthogonal function analysis is a multivariate temporal analysis technique that can be used to identify sources of variance in patient data and what physiological parameters vary together.

During the second quarter we set out to determine the best way to present empirical orthogonal function (EOF) results to clinicians to denote patient state changes and identify variables accounting for the variance. Data

preprocessing was an essential first step to applying this technique and we addressed two characteristics of the data, specially outlier removal and missing data. As a result of the fact that the physiological data collected in the Neurological ICU is not collected in a controlled environment, there are frequent outliers that represent spurious data from the perspective of patient care. For example, catheters measuring body temperature are often removed prior to the termination of data collection leading to temperature readings in both the body temperature range as well as temperature readings in the room temperature range. We confronted difficulties leveraging existing computational tools given the high levels of missingness in our datasets. We explored interpolation and matrix factorization methods for imputing missing values in the multidimensional setting. We also explored custom extensions to existing matrix factorization methods to adapt them to time series and potentially identify spurious outliers simultaneously. The best procedure we found was to implement a variational Bayesian mixture model for the detection and removal of such spurious states – the results of which applied to the same variable (temperature) can be seen in the figure 1.

**Figure 1. Unfiltered (top) versus filtered (bottom) temperature values**




Empirical orthogonal function (EOF) analysis is designed to identify and highlight the set of variables that are contributing most to the variability of a patient's state during a given time period. [4,5] This analysis can be used both for visualizing the patient's state over time, but can also be used to identify points of significant change. Practically, due to the fact that many physiological variables are not always recorded, we had to first address the issue of missingness. Although, we experimented with several approaches, the combination of outlier removal as described above and constant interpolation was determined to be the most accurate approach. We have performed the EOF analysis on 2 fully anonymized patient datasets. A brief period from one of these patients is displayed in figure 2 highlighting a period of significant change where temperature is one of the variables involved in this change.

**Figure 2. EOF Analysis (top) and temperature (TMP-2; bottom) values**

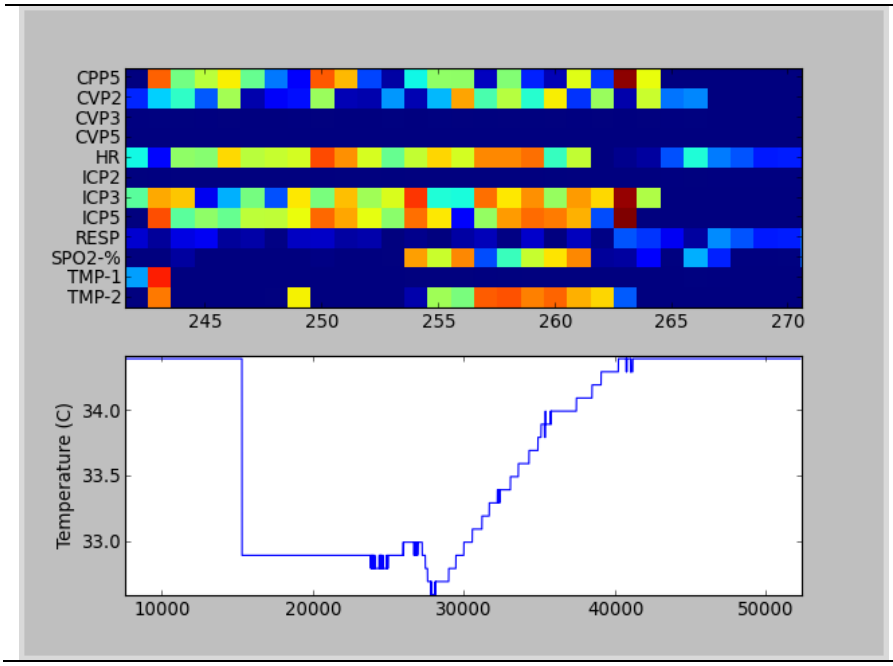
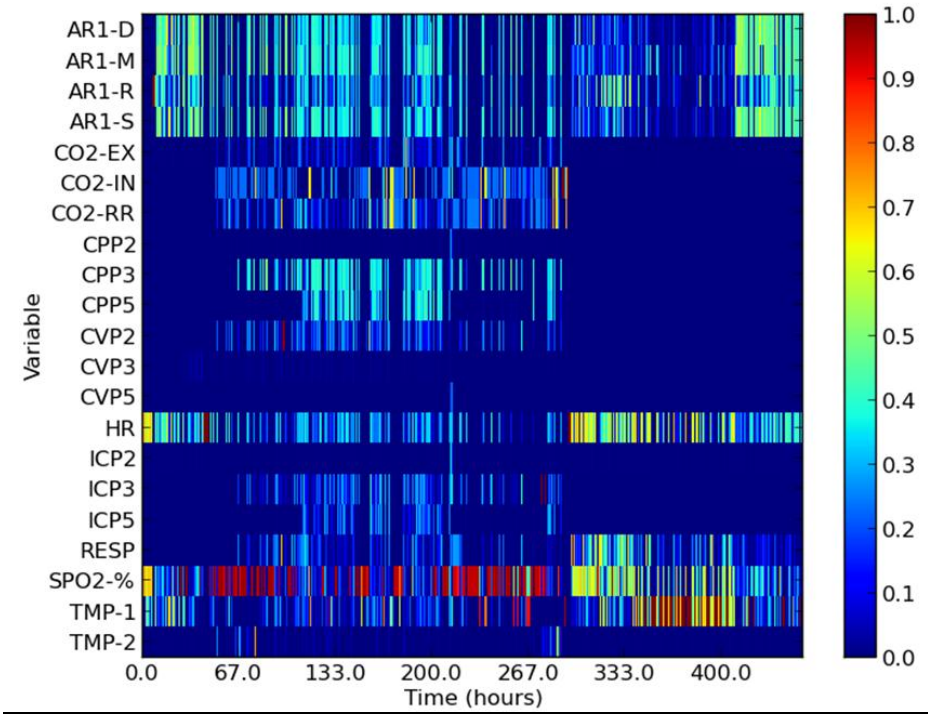


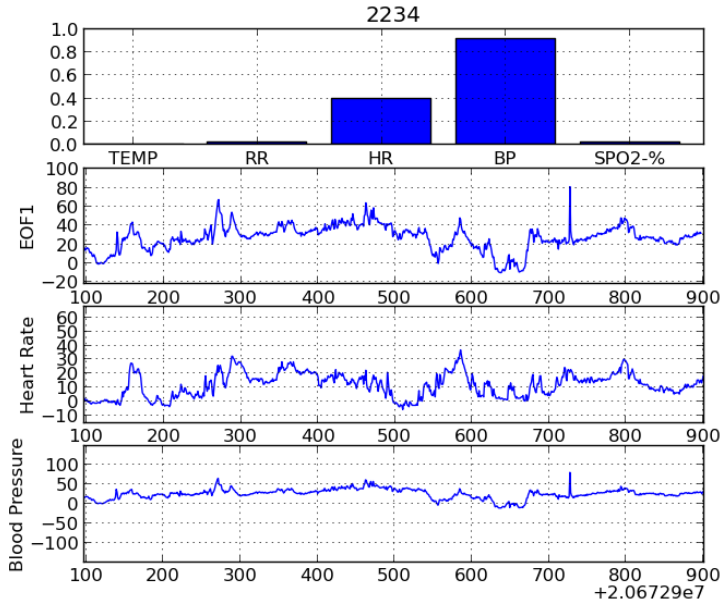
**Figure 3. EOF Analysis Results for Individual Patient**




Several steps are required to apply EOF to physiologic data. The raw data must be visualized and preprocessed on a per-variable basis with variational Gaussian mixture models for outlier removal. Interpolation is then used to create a uniformly sampled time series based on the original series. Data is separated across all variables into time bins and for each bin the primary eigenvector is calculated. This represents the unitized linear combination of variables that explains the most variance for the bin. Each patient's primary eigenvector for each time bin can be visualized on a heatmap (See Figure 3.)

We quickly discovered that while heatmaps accurately represented the varying relationships among all the parameters that it would be difficult to use this information to determine if the patient was changing in ways that required attention. This is a key point of learning and emphasis, specifically that visualizing relationships among patient data parameters accurately does not in itself solve the real problem of helping clinicians make better decisions from patient data. At best this heatmap requires significant effort on part of the users to extract meaningful information from it. Data visualization in itself then is not sufficient and we thereafter added the requirement that an analysis must both represent the relationships among parameters and convert this information into a form that fits into the mental framework of clinicians.

**Figure 4. EOF Composite Score for Individual Patient**



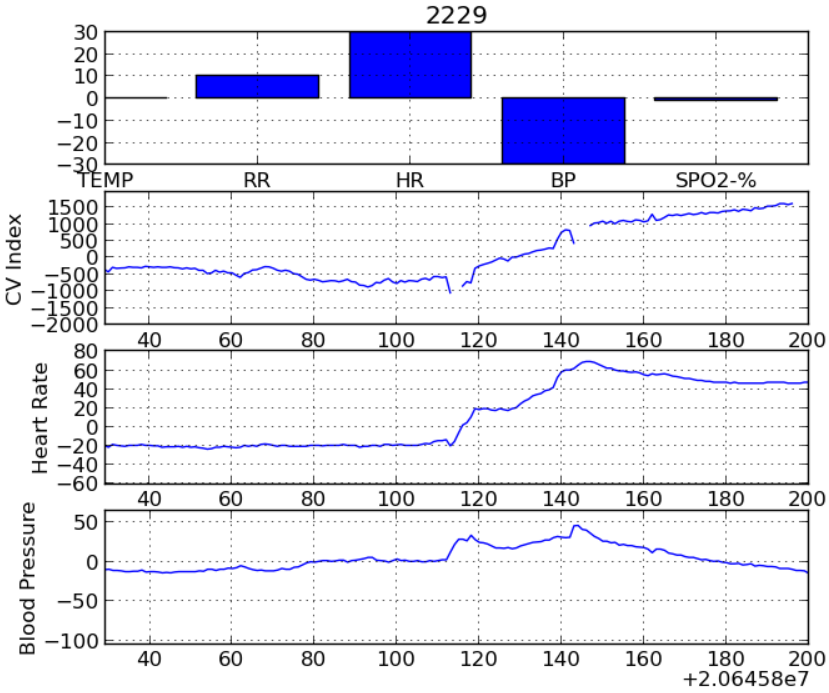

From top to bottom: The variable weightings for the first EOF, the projection of the first EOF onto patient 2234's multivariate time series, patient 2234's heart rate time series and patient 2234's blood pressure time series.

In the second and third quarter we worked to determine the best way to present results to clinicians to denote patient state change and to highlight what variables account for this variance. We expanded our approach to include an alternative method of applying EOF analysis. In contrast to the method that we previously described, this method evaluated the directions in the space of measured variables that explains the most variance over all time for all patients. The initial method we outlined evaluates a similar

quantity for small time bins in a patient specific manner. The new technique discovers the weighting on the measured variables that are most meaningful for explaining the variation from time to time within a patient and across patients. We will explore the interpretability of these directions in the space of measured variables and leverage these discovered directions to create composite clinical scores for each dimension. These composite clinical scores will be evaluated for their clinical utility. See Figure 4 for an example principal EOF weighting along with the composite score for patient 2234. The principal EOF seems to capture the sympathetic response with an increase in heart rate and blood pressure. This can be seen in Figure 4 from minute 200 to minute 450. During this time period rises in both blood pressure and heart rate lead to a rise in the principal EOF.

This method can be extended. Instead of allowing the statistics of the data to determine the most meaningful weightings as described above, it is also possible to choose what should be an a priori meaningful weighting. We focused on cardiovascular collapse as well as respiratory distress. We leverage clinical knowledge to identify cardiovascular collapse as a scenario where blood pressure is falling and other vitals signs such as heart rate and respiratory rate are rising. For example it is well known that patients headed for septic shock start to have drops in blood pressure while heart rate increases. In practice these subtle changes over hours can be

**Figure 5. EOF Composite Score for Cardiovascular Collapse**




A pre-specified weighting corresponding to cardiovascular collapse that is demonstrated during a portion of patient 2229's time series. From top to bottom: The cardiovascular collapse variable weightings, the projection of the weightings onto the multivariate patient time series to create the CV Index, patient 2229's heart rate time series, and patient 2229's blood pressure time series.

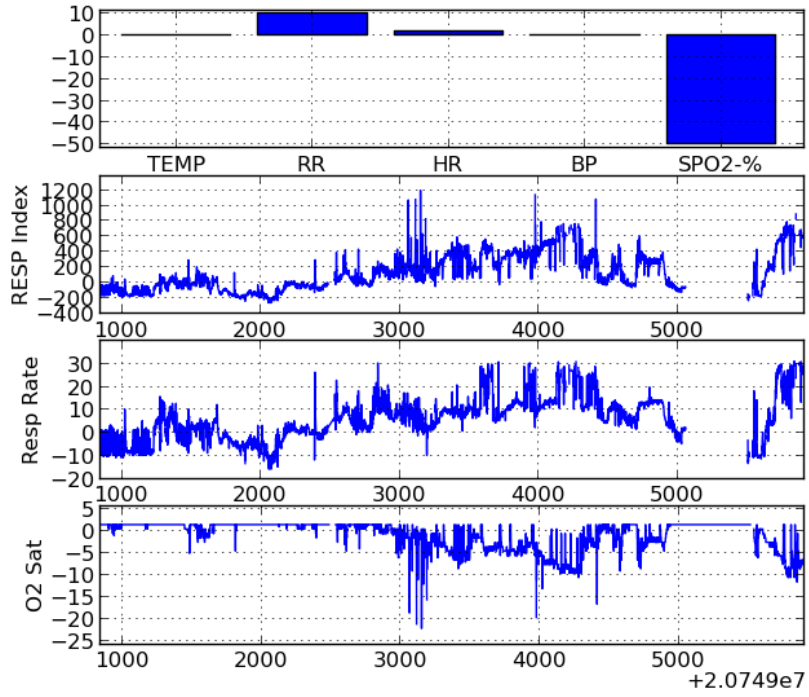



Figure 5b. A pre-specified weighting corresponding to respiratory distress that is demonstrated during a portion of patient 2247's time series. From top to bottom: The respiratory distress variable weightings, the projection of the weightings onto the multivariate patient time series to create the Resp Index, patient 2247's respiratory rate time series, and patient 2247's oxygen saturation time series.

difficult to pick up by clinicians because heart rate and blood pressure are typically in the normal ranges until the patient is on the verge of shock. For example Figure 5 (top) demonstrates that at approximately minute 120, the patient's heart rate rises while blood pressure rises moderately, followed by a stabilization of heart rate and a decline in blood pressure. During both of these phases, the CV index rises. Also, for respiratory failure, we identify that scenario by a decreasing oxygen saturation, decreasing respiratory rate, and increasing heart rate. Figure 5 (bottom) demonstrates that from approximately minute 2000 to minute 4000, patient 2247 experienced increasing respiratory distress marked by a gradually increasing respiratory rate and a gradually decreasing oxygen saturation. The RESP Index captures these changes with a rising value over this time period.

We believe there are several benefits to this approach including: 1) it captures clinically relevant changes across physiologic parameters; 2) it may be generalized to any number of parameters and patterns deemed important to monitor for; 3) it presents the results to clinicians as an index that can be tracked over time fitting the existing cognitive model in intensive care; and 4) results can also be displayed in an overview format showing many patients at once. During the cognitive experiment we will test these hypotheses and evaluate the perceived helpfulness of these indices to clinicians to identify patient change that may precede clinical deterioration. Figure 6 shows the iterations of the overview page to help clinicians identify which patients need attention first. However, any results would need to be tempered until clinical studies can be conducted to determine if specific indices are associated with clinical conditions and to determine values for indices that may represent different categories of clinical risk that should be monitored for.

**Figure 6. EOF Composite Score Overview Format**

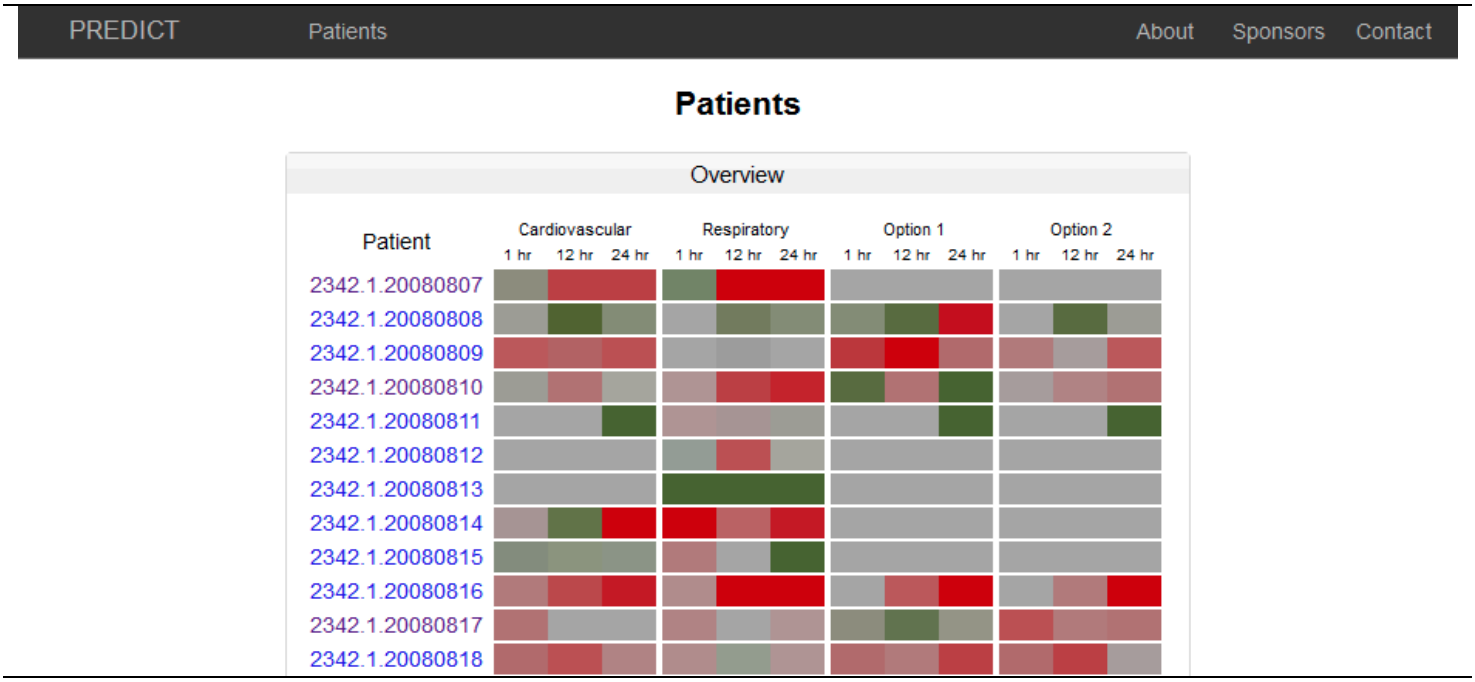



Figure 6. The patient overview page provides clinicians 1 hour, 12 hour, and 24 hour windows for change on two pre-specified and two unspecified EOF clinical indices. We will test in a cognitive experiment whether clinicians are able to identify patients that need attention first using this approach.

## *SEPSIS VISUALIZATION*

The goal of the SIRS (Sepsis) visualization is to help clinicians identify the physiological signs leading to sepsis. This is challenging for clinicians because with sepsis there are a series of 5-6 variables, sometimes more, (HR, HRV, Respiration Rate, Temp, WBC (and bands), BP) that can be used as indicators – perhaps early indicators – of a patient going into septic shock. Generally, if two or more criteria are met, there is a suspected infection.

1) temperature >38ºC or lower than 36ºC;
2) heart rate > 90 beats/min;
3) respiratory rate > 20 breaths/min; and
4) white blood cell count > 12,000/mm3 or < 4,000/mm3 which more than 10% immature forms.

At Columbia, clinicians monitor 6 variables (4 SIRS criteria, and 2 additional):

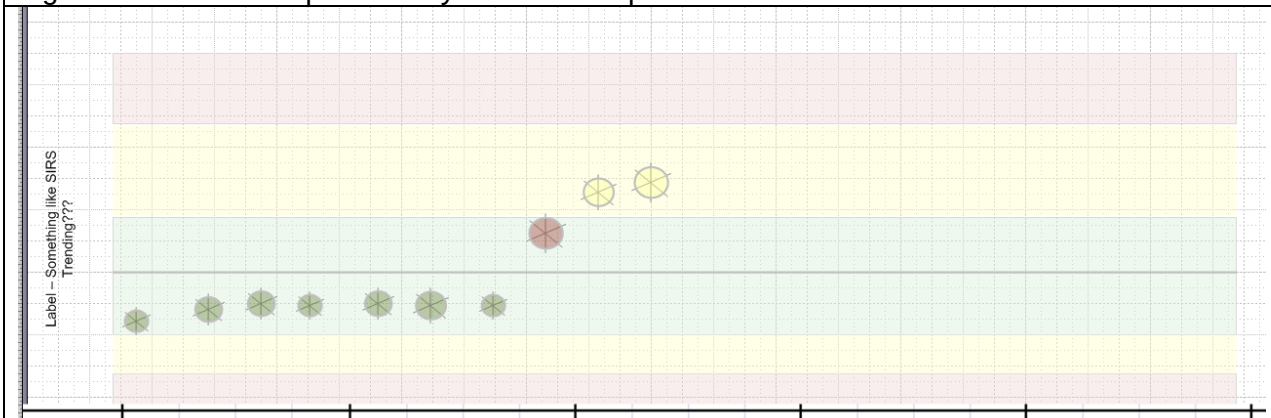
1) temperature
2) heart rate
3) respiratory rate
4) white blood cell count
5) heart rate variability
6) blood pressure

The challenge is that once these criteria are met, it is often the case that the patient is severely ill. It is possible that we can help to detect the early emergence of sepsis through supporting clinicians in seeing early trends in SIRS-related variables. The most difficult part (for clinicians) of detecting (early detection) that a patient is potentially going into septic shock is in seeing the slight trending of multiple variables at one time. Not a single variable spiking, but instead, it is the trend of all variables. The early trend of these variables that we want to support is that temp, HR, RR, and WBC go up and HRV and BP go down. Typically, these variables change close to the same time.

For clinicians, the challenge is the monitoring for these slight trends in multiple variables are multifaceted:

1) Monitoring for the emergence semi-rare events with weak evidence is challenging.
2) The variables that the clinicians are monitoring are not all located in the same place.
3) It is easy to see many of the variables on the patient monitor (HR, RR, Temp), however that monitor only provides the last 10 seconds of data. Longer trends are not shown here.
4) Rate of change of individual variables is not easily found
5) Rate of change of multiple variables requires integration in the clinician or nurses head.

Figure 7. Initial Mockup to identify SIRS and sepsis




| | 0:00 | 0:15 | 0:30 | 0:45 | 1:00 | 1:15 | 1:30 | 1:45 | 2:00 | 2:15 | 2:30 | 2:45 | 3:00 | 3:15 | 3:30 | 3:45 | 4:00 | 4:15 | 4:30 | 4:45 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| HRV | 4 | 3 | 2 | 1 | 2 | 2 | 2 | 4 | 6 | 3 | 5 | 3 | 4 | 6 | 8 | 5 | 4 | 6 | 4 | 3 |
| BP | 120 | 122 | 121 | 120 | 123 | 125 | 122 | 124 | 120 | 122 | 121 | 120 | 123 | 125 | 122 | 124 | | | | |
| HR | 65 | 66 | 62 | 63 | 65 | 66 | 62 | 63 | 65 | 66 | 62 | 63 | 65 | 66 | 62 | 63 | 65 | 66 | 62 | 63 |
| Resp Rate | 22 | 23 | 23 | 22 | 23 | 24 | 25 | 22 | 22 | 23 | 23 | 22 | 23 | 24 | 25 | 22 | 22 | 25 | 26 | 28 |
| Temp | 35 | 35.2 | 32.4 | 33.5 | 35 | 35.2 | 32.4 | 33.5 | 35 | 35.2 | 32.4 | 33.5 | 35 | 35.2 | 32.4 | 33.5 | 35 | 35.2 | 32.4 | 33.5 |
| WBC | | | | 44 | | | | | | | | | | | | 42 | | | | |
| Combined | | | | | | | | | | | | | | | | | | | | |

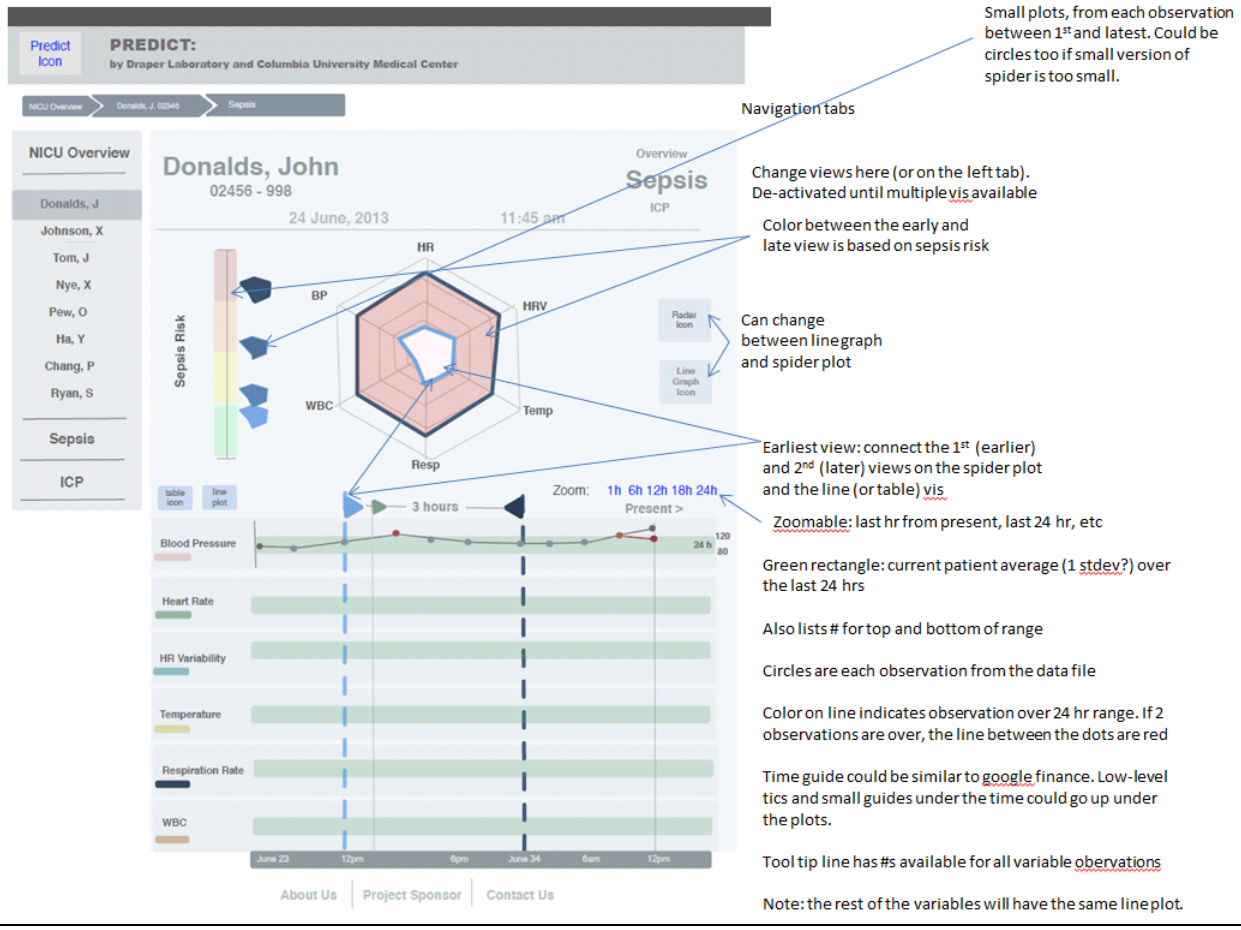
In the initial mockup the circle (Figure 7) was not actually meant to be read (no individual variables or numbers). We believed that showing an increasing size (and color and position) could be used to easily indicate to clinicians that SIRS is emerging. The clinician or nurse can then dig deeper into the actual numbers and notice how those numbers are changing over time. The circle is simply an alerting mechanism. There are several reasons why we wanted a simple user interface. In this case two variables trend down while four trend up when a patient is becoming septic. Secondly this UI is new and therefore we simply wanted to grab the clinician's attention and direct it to a potential event as evidenced by these SIRS variables changing in a bad direction. It would then be up to the clinician to dig into the trends and order more tests (if necessary). The objective in this version of the mockup was to:

- Present all 6 variables in a single location
- Present longer trends of all variables
- Show their individual values at time steps of 15-minutes.
- Color code the individual values to indicate how close they are to normal or alarm stages.

As we explored this design further however we changed it significantly from the original mockup. The change in design (Figure 8) was prompted by several concerns with the original design including:

1. The presentation of the individual variables and numbers would not reduce clinician cognitive load.
2. Clinicians would have to trend many hours of data to determine if changes were occurring, again potentially not positively impacting clinician cognitive load.
3. The current design maximizes the effect of a making a single comparison between the current status and past status and should be more effective at reducing cognitive load.
4. The current design still presents all 6 variables in a single location and allows the evaluation of longer trends of all variables.

Figure 8. Stage 2 of Sepsis Mockup




The design continued to evolve in the fourth quarter. We incorporated a shock-index graph. The shock-index is a metric that has been shown in studies to be helpful in identifying patients at high risk for sepsis. A number of changes were added (Figure 9):

1. Addition of the shock index. The shock index is a derived value that can be used to indicate potential sepsis severity. Completed first version of the shock-index graph. Whether the y-axis should be linear or logarithmic is an area of further investigation.

2. We reworked the observation graphs and the shock-index graph so all use the same underlying time-series graph. This was necessary to facilitate a single cursor across all the time-series charts (shock-index and observation graphs).

3. Normalization of the sepsis indicator: The sepsis indicator is a normalized value. The normalization requires some tweaking to ensure that it can pick up increases to sepsis

4. Visualization of timelines requires additional input to show relative increases in numbers as well as the numbers themselves.

5. Changed the "change" chart to use a red-gray-green color scheme. The color selection will be centralized so that the "change" chart, the patients overview, and possible others use the same "change-based" semantic classifications and colors.

6. Warning areas for specific parameters are highlighted in yellow and red based on parameter specific thresholds. The EOF indices will have a pop-up showing the bar graph to help with interpretation. The design allows for variables to be added or removed without requiring changes to the interface.

Figure 9. Sepsis Visualization Tool

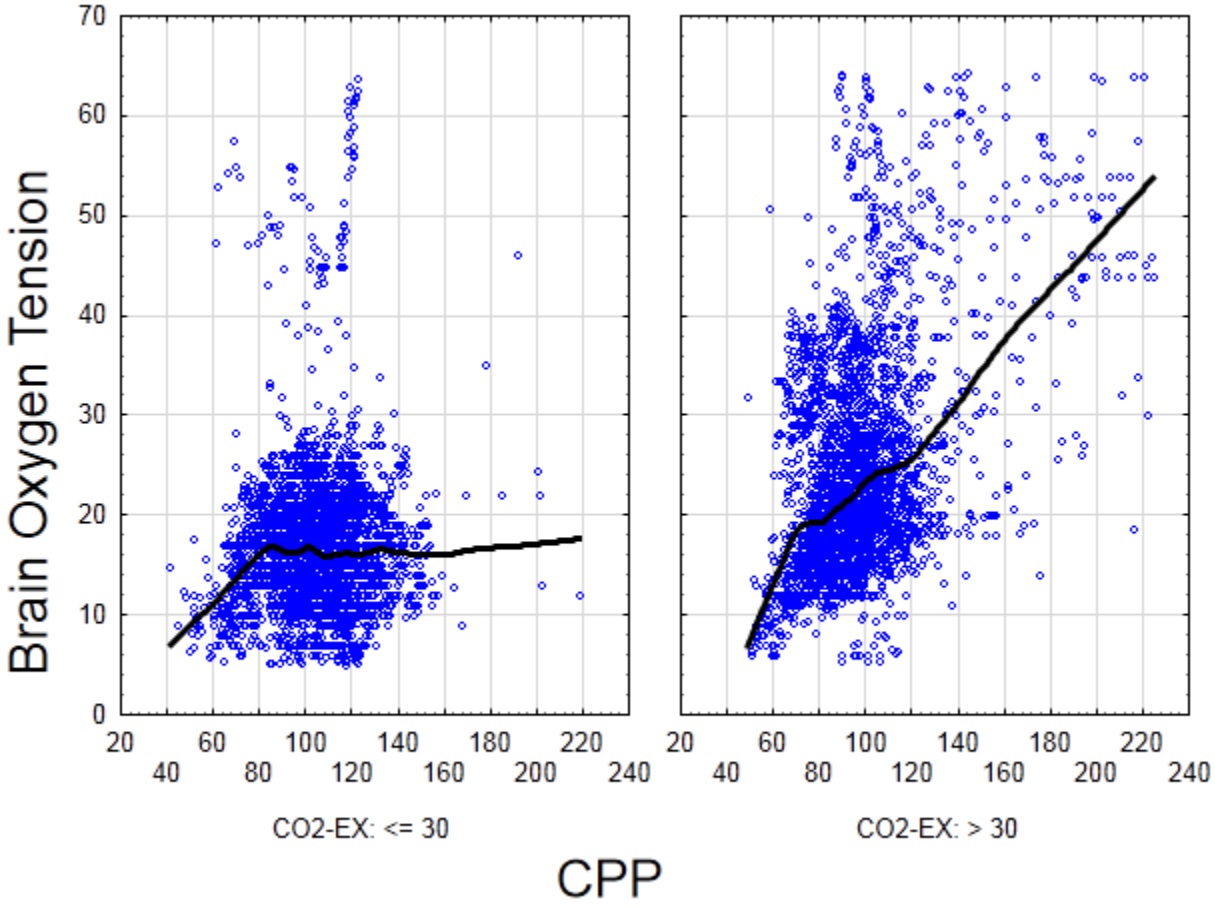

The PREDICT interface displays meaningful information about changes in patient state. Clockwise from top left is patient information, current risk levels for physiological systems, an integrated view of the current Septic Shock Index, and the bottom timeline graph displays trends and allows drilling into patient history.

## *INTRACRANIAL PRESSURE MANAGEMENT*

The goal and purpose of the intracranial pressure management interactive visualization is to determine an 'ideal' target for cerebral perfusion pressure that will maintain adequate perfusion of the brain. The clinical task is to determine an 'ideal' target for cerebral perfusion pressure that will maintain adequate perfusion of the brain (e.g., [6-8]). Figure 10 displays data from a single patient and highlights the complexity of interpreting patient monitoring data without visualization as the relationship between cerebral perfusion pressure (CPP) and brain oxygen tension is dependent on end tidal CO2 concentrations. When end tidal CO2 is below 30 the

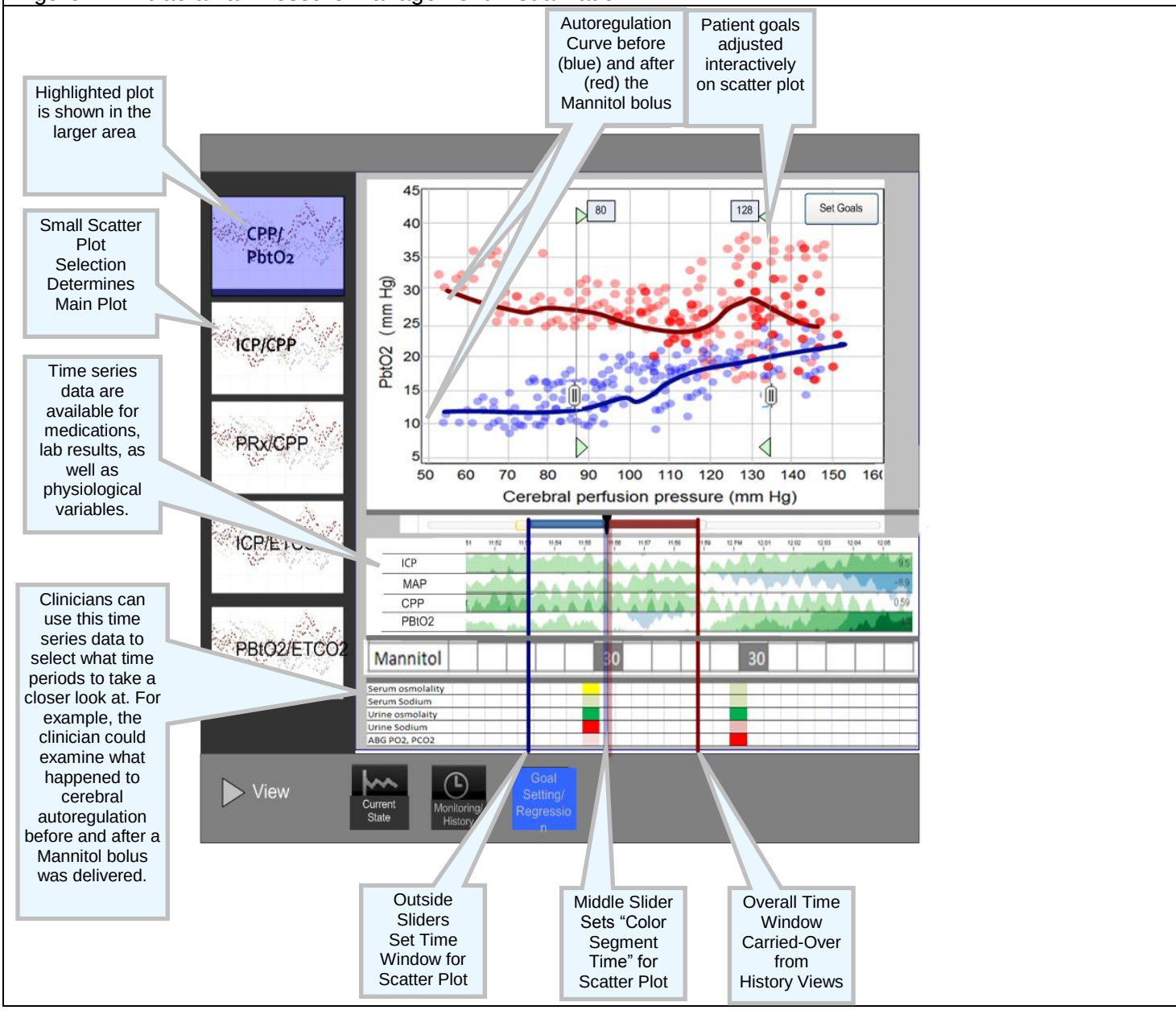
patient appears to have relatively intact cerebral autoregulation, which is to say that vascular systems that regulate cerebral blood flow to a constant flow rate are functioning properly when CPP is greater than 80 mmHg. Note the locally weighted regression line is essentially flat when CPP is greater than 80 mmHg, but steadily declines below that pressure. In contrast, when end tidal CO2 is above 30 we observe cerebral autoregulation failure when brain oxygen tension increases as cerebral perfusion pressure increases. These relationships are impossible to determine without tools to visualize high resolution physiologic data, which are largely not available at the bedside.

Figure 10: Interpretation of multimodal data to identify cerebral perfusion pressure targets



The figure below (Figure 11) presents the prototype of the ICP tool.

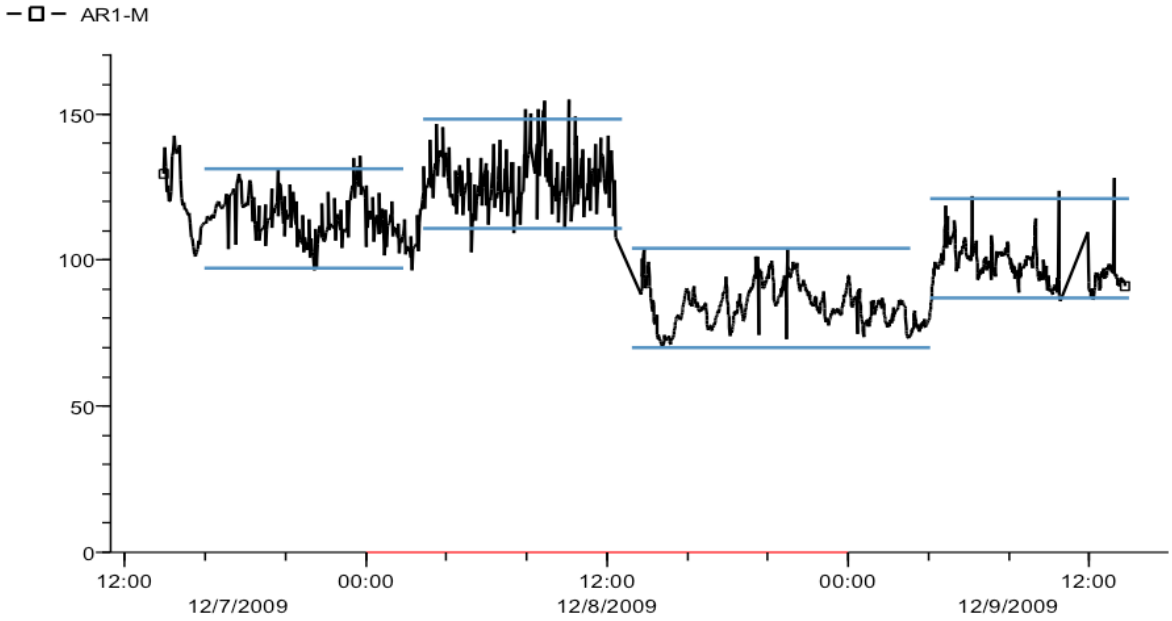
Figure 11. Intracranial Pressure Management Visualization



## *REAL-TIME VISUALIZATION DEMONSTRATION*

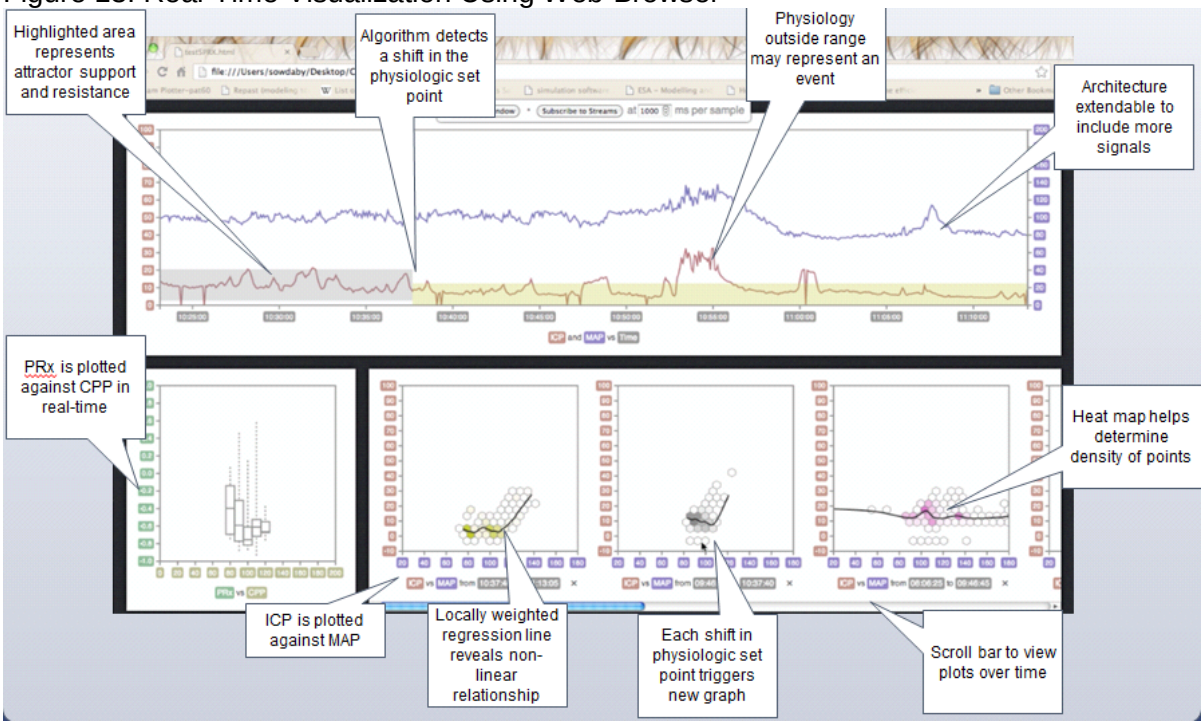
We have started to develop a working real-time demo that incorporates the principles of the three visualizations. Chaos theory describes the behavior of attractors in dynamical systems such as in human physiology. In practice physiology varies around a physiologic set point until the system is perturbed to a new set point. These ranges can be identified utilizing financial time series support and resistance formulas (Figure 12).

Figure 12. Identification of Short-Term Normal Range of Parameters



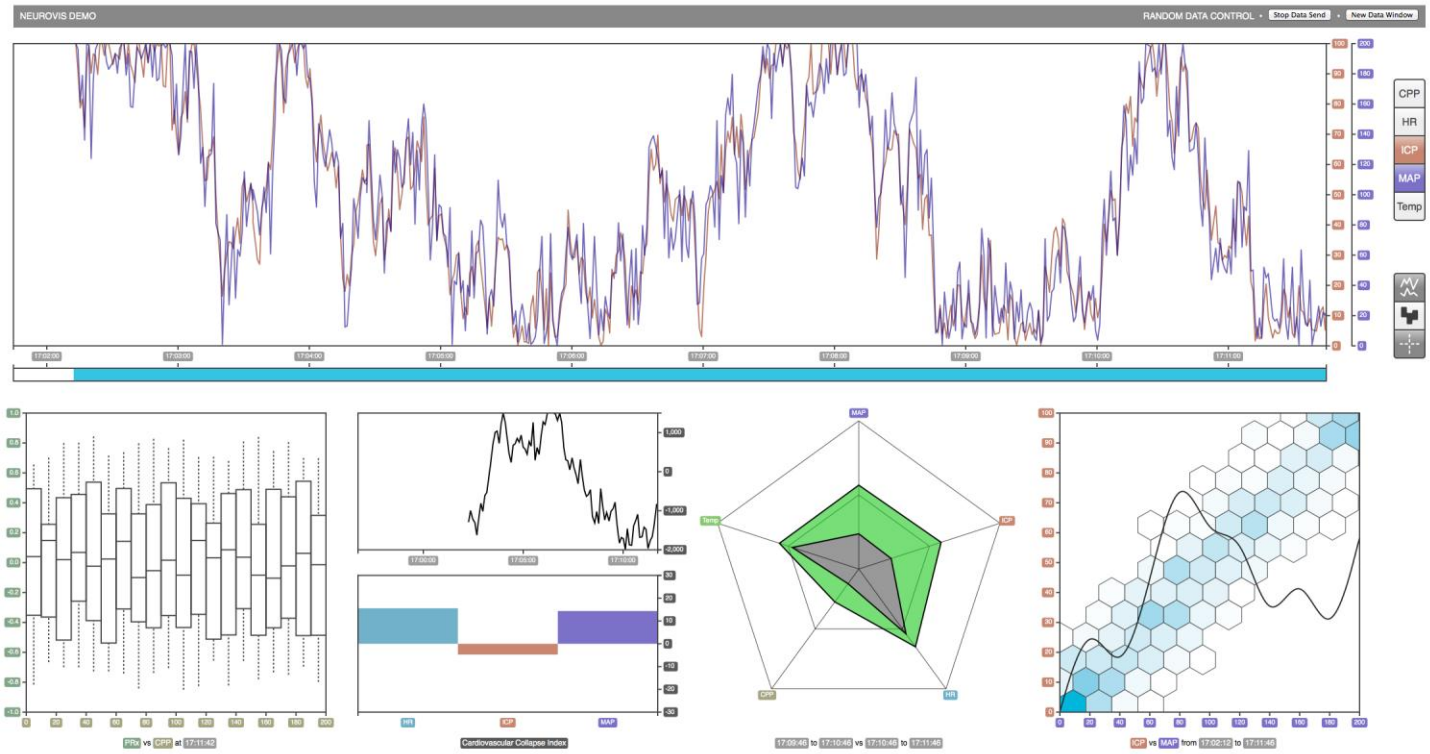

Assessment of cerebral autoregulation using the pressure reactivity index (PRx) is a common application of multimodal neuromonitoring data. We have developed a demonstration real-time web application to enable clinicians to assess cerebral autoregulation status and identify potential patient state changes in real-time at the bedside (Figure 13). We have uploaded a movie that demonstrates this functionality (Appendix 1).

Figure 13. Real-Time Visualization Using Web-Browser



In addition we have modified the basic design to accommodate multiple data streams and visualizations from different tools being developed. In Figure 14, we have included elements from both the overview and sepsis visualization prototypes into a single tool (Figure 14). This can be viewed using simulated data on http://demos.imateapot.net/neurovis/bedview.php. **This is hosted on a low traffic web server that can only support one to two simultaneous connections, so please do not widely distribute this link at this time.**

Figure 14. Incorporation of Visualization Elements




## *COGNITIVE EXPERIMENT*

Phase 2 of the project has begun and its objective is to conduct a cognitive experiment to test whether the visualization improves clinician decision making. We are recruiting physicians at three levels of training to participate in this study. This includes faculty that have completed residency and fellowship in neurocritical care, as well as fellow and resident trainees. To date we have consented three faculty and five residents to participate. Seven clinical fellows have not yet been approached to participate.

### *Overview*

Physicians are presented a clinical vignette with data and asked to identify the frequency of physiologic events, assess overall patient status, identify tests and treatments they would order, and report the likelihood that clinical events have occurred or will occur in the next 24 hours.

### *Design*

The mode of physiologic data presentation (visualization versus text) and clinical event type (sepsis versus other events) are the two independent variables. Several hypotheses are tested: 1) The speed and accuracy of responses are better when physiologic data is presented in a visualization versus a text spreadsheet; 2) Clinical events are more likely to be detected in advance of onset in the visualization versus text condition; 3) sepsis detection specifically is improved when using data visualization. To test these hypotheses clinical vignettes were generated from actual clinical cases of 3 patients experiencing sepsis and 3 experiencing clinical events other than sepsis. A vignette was created for each patient for the day the clinical event occurred, and for each of the 2 days leading up to the event day. Each patient day is presented in both visualization and text form for a total of 36 (6 patients x 3 patient days x 2 conditions) vignettes.

The two most likely threats to the internal validity of the study were clinicians recognizing that clinical cases were presented in both text and visualization conditions, and that clinical events were likely to occur on the 3rd

day of the case. Specifically, if unaltered, the same history of present illness would be presented six times, and the clinical exam and labs for each patient day would be presented with physiologic data in text and visualization conditions. To control for these potential internal validity threats, we generated six versions of the history of present illness and two versions of the clinical exam and labs information. This was done in a manner that made it unlikely that the case would be recognized while maintaining the clinical meaning of the presentation. In the instruction, participants are told that they would be presented "a series of similar cases" to reduce questions about the similarity of patients. In total, clinicians are presented 36 vignettes that appear to be created from 36 different patients, although in reality come from 6 patients. Figure 15 shows an example of these modifications for the same patient day.

Figure 15. Patient Vignette Modified for Visualization and Text Conditions.

**Version 1**

**History of Present Illness:**

67 year old woman with diabetes on daily baby aspirin who presented to an outside hospital with neck pain and altered mental status. CT imaging showed subarachnoid hemorrhage. She was then transferred to CUMC where repeat imaging showed intraventricular hemorrhage (Hunt Hess 3, Fisher grade 4, modified Fisher grade 4), and mild hydrocephalus. She was admitted to the Neuro ICU for further monitoring where digital subtraction angiography was negative for aneurysms, and an EVD was placed.

**Post-bleed day 9**

**Physical exam:**

- Lungs with bilateral crackles in bases
- Normal cardiac exam
- Abdomen soft, nontender, nondistended, bowel sounds present
- Mildly erythematous R upper extremity, mild swelling

**Neuro exam:**

- Asleep, eyes closed; responds to noxious stimulation only, follows commands
- PERRL
- Localizes with both UE to noxious stimuli; withdraws with both LE to noxious stimuli

**Version 2**

**Patient Vignette**

**History of Present Illness:**

64 year old woman with HTN and DM2 who was admitted to the CPMC NICU with Hunt & Hess Grade 3, Fisher Grade 4, modified Fisher grade 4 subarachnoid hemorrhage with early hydrocephalus. CT angiography showed no aneurysms nor evidence of radiographic vasospasm, and no aneurysm was seen on conventional angiogram. On arrival to the NICU, she underwent EVD placement for hydrocephalus.

**Post-bleed day 13**

**Physical exam:**

- Eyes open spontaneously; constant stimulation is necessary to keep awake
- Oriented to date; perseverates
- Cranial nerves intact
- Moves all 4 extremities equally and antigravity

**Imaging:**

- CXR with worsened pulmonary edema

**24 Hour Labs:**

- CSF extracted from EVD: G68 P127 618 WBC, 893 RBC

The survey is estimated to take approximately three to four hours to complete. The survey is broken down into three sessions of 12 patient vignettes. Study participants may also stop between cases within a survey. Balancing was used to generate the list of patient case days contained in each survey (Table 1). Lastly, participants take a 10 minute survey to evaluate the overview visualization in which clinicians are presented a single visualization and asked to identify the three patients they would round on first and last.

### *Procedure*

Physicians are presented a clinical vignette and are provided the history of present illness, clinical exam information and standard laboratory tests for the current patient day. Physiologic data is then presented in either a text spreadsheet similar to what is used in an electronic medical record or in the visualization. With this information participants are asked to identify the frequency of physiologic events, assess overall patient status, identify tests and treatments they would order, and report the likelihood that clinical events have occurred or will occur in the next 24 hours. Responses to each question are timed allowing speed and accuracy to be determined. A case used in the experiment is shown Figures 16-21.

Table 1. Balancing presentation of case days in three surveys by condition

| Control Condition | Patient | Patient Day | Visualization | Text |
|---|---|---|---|---|
| | N01 | -2 | Survey 1 | Survey 2 |
| | N01 | -1 | Survey 2 | Survey 3 |
| | N01 | Event (0) | Survey 3 | Survey 1 |
| | N02 | -2 | Survey 2 | Survey 3 |
| | N02 | -1 | Survey 3 | Survey 1 |
| | N02 | Event (0) | Survey 1 | Survey 2 |
| | N03 | -2 | Survey 3 | Survey 1 |
| | N03 | -1 | Survey 1 | Survey 2 |
| | N03 | Event (0) | Survey 2 | Survey 3 |
| **Sepsis Condition** | **Patient** | **Patient Day** | **Visualization** | **Text** |
| | S01 | -2 | Survey 3 | Survey 1 |
| | S01 | -1 | Survey 1 | Survey 2 |
| | S01 | Event (0) | Survey 2 | Survey 3 |
| | S02 | -2 | Survey 2 | Survey 3 |
| | S02 | -1 | Survey 3 | Survey 1 |
| | S02 | Event (0) | Survey 1 | Survey 2 |
| | S03 | -2 | Survey 1 | Survey 2 |
| | S03 | -1 | Survey 2 | Survey 3 |
| | S03 | Event (0) | Survey 3 | Survey 1 |

Figure 16. Initial patient vignette

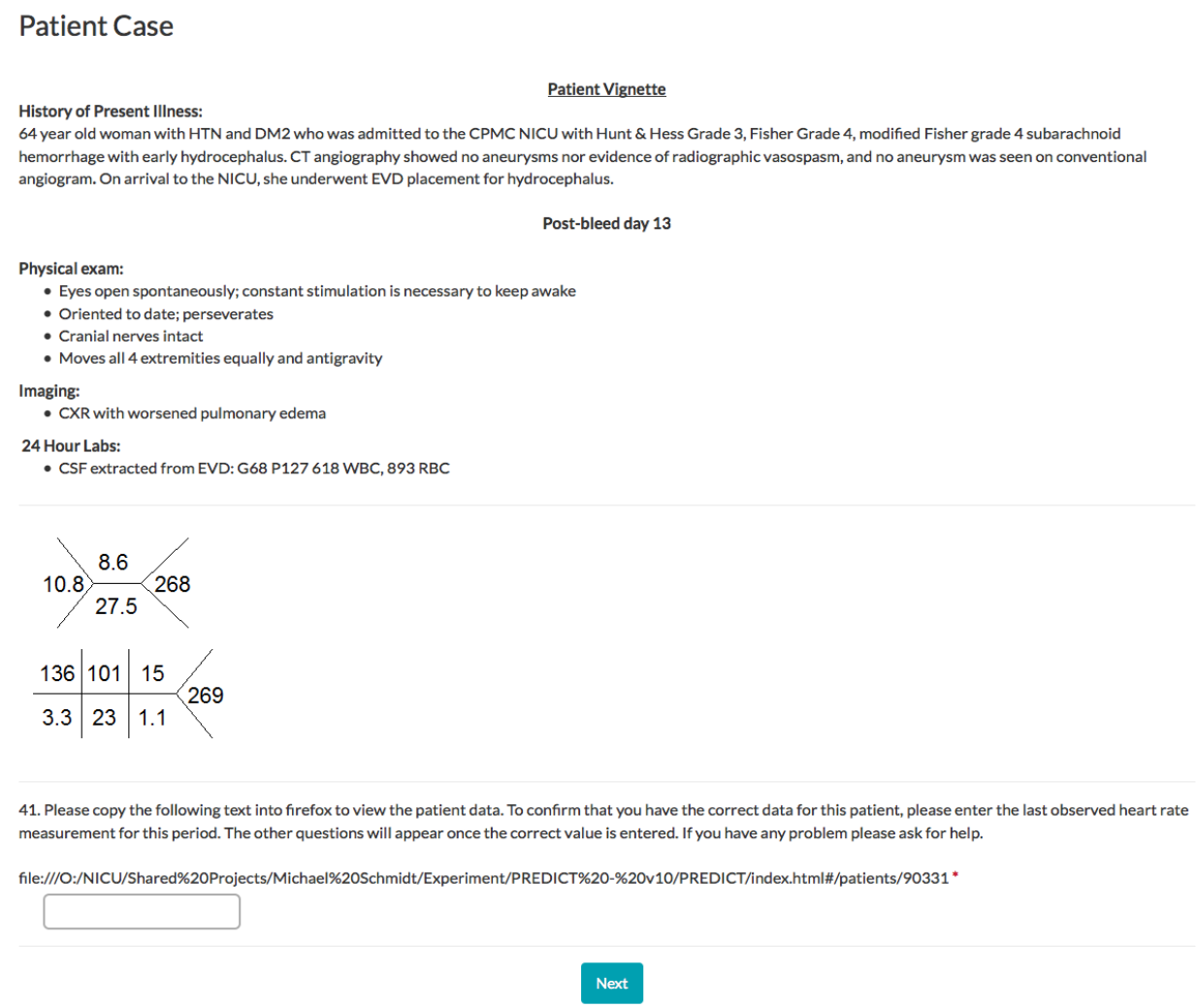


Figure 17. Patient data presented in visualization


Figure 18. Patient data presented in text spreadsheet

| Time | 20:00 | 21:00 | 22:00 | 23:00 | 0:00 | 1:00 | 2:00 | 3:00 | 4:00 | 5:00 | 6:00 | 7:00 | 8:00 | 9:00 | 10:00 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Shock Inc | 0.4 | 0.53 | 0.37 | 0.32 | 0.33 | 0.52 | 0.47 | 0.47 | | | | 0.48 | 0.47 | 0.57 | 0.46 |
| cv | -1.14 | -0.4 | -1.96 | -2.01 | -1.86 | -0.08 | -0.35 | -0.41 | | | -0.94 | -0.23 | -0.5 | 0.23 | -0.36 |
| resp | 1.35 | 1.03 | 2.62 | -0.49 | -0.09 | -0.33 | -0.48 | -0.13 | | | -0.99 | -1.09 | -0.99 | -0.12 | -1.41 |
| eof1 | 0.91 | 0.47 | 2.29 | 1.78 | 1.67 | -0.35 | -0.12 | 0.06 | | | 0.56 | -0.41 | 0.06 | -0.91 | -0.35 |
| eof2 | -4.04 | -2.78 | -5 | -0.06 | -0.13 | -0.06 | -0.08 | -0.1 | | | 0.09 | -0.05 | 0.07 | -2.14 | -0.01 |
| HR | 66 | 81 | 79 | 64 | 64 | 65.5 | 63 | 65 | | | 65 | 59 | 65 | 60 | 58 |
| SBP | 167 | 153 | 215 | 197.5 | 194 | 125 | 133 | 139 | | | | 123 | 139 | 106 | 125 |
| MAP | 93 | 91 | 146 | 144 | 140 | 73.5 | 77 | 79 | | | | 73 | 85 | 64 | 75 |
| RR | 21 | 18 | 28 | 20 | 24 | 22 | 21 | 23 | | | 15 | 15 | 15 | 14 | 12 |
| SPO2 | 96 | 97 | 95 | 100 | 100 | 100 | 100 | 100 | | | 100 | 100 | 100 | 98 | 100 |
| TEMP | | | | | | | | | | | | | | | |
| CO2-EX | | | | | | | | | | | | | | | |
| ICP | 17 | 6 | 11 | 9 | 15 | | 23 | 12 | | | | 8 | 17 | 17 | 15 |
| WBC | 7.2 | | | | | | | | | | | | | | |

Figure 19. Survey questions: identify events, patient status, tests, and orders

42. Which events occurred during the time period shown? *

| | Never occurred | < 1 hour | 1 - 3 hours | 3 - 12 hours | > 12 hours | Unavailable/Unknown |
|---|---|---|---|---|---|---|
| Tachycardia | ○ | ○ | ○ | ○ | ○ | ○ |
| Bradycardia | ○ | ○ | ○ | ○ | ○ | ○ |
| Fever | ○ | ○ | ○ | ○ | ○ | ○ |
| Hypothermia | ○ | ○ | ○ | ○ | ○ | ○ |
| Hyperventilation | ○ | ○ | ○ | ○ | ○ | ○ |
| Hypoxia | ○ | ○ | ○ | ○ | ○ | ○ |
| Hypertension | ○ | ○ | ○ | ○ | ○ | ○ |
| Hypotension | ○ | ○ | ○ | ○ | ○ | ○ |
| ICP elevation | ○ | ○ | ○ | ○ | ○ | ○ |

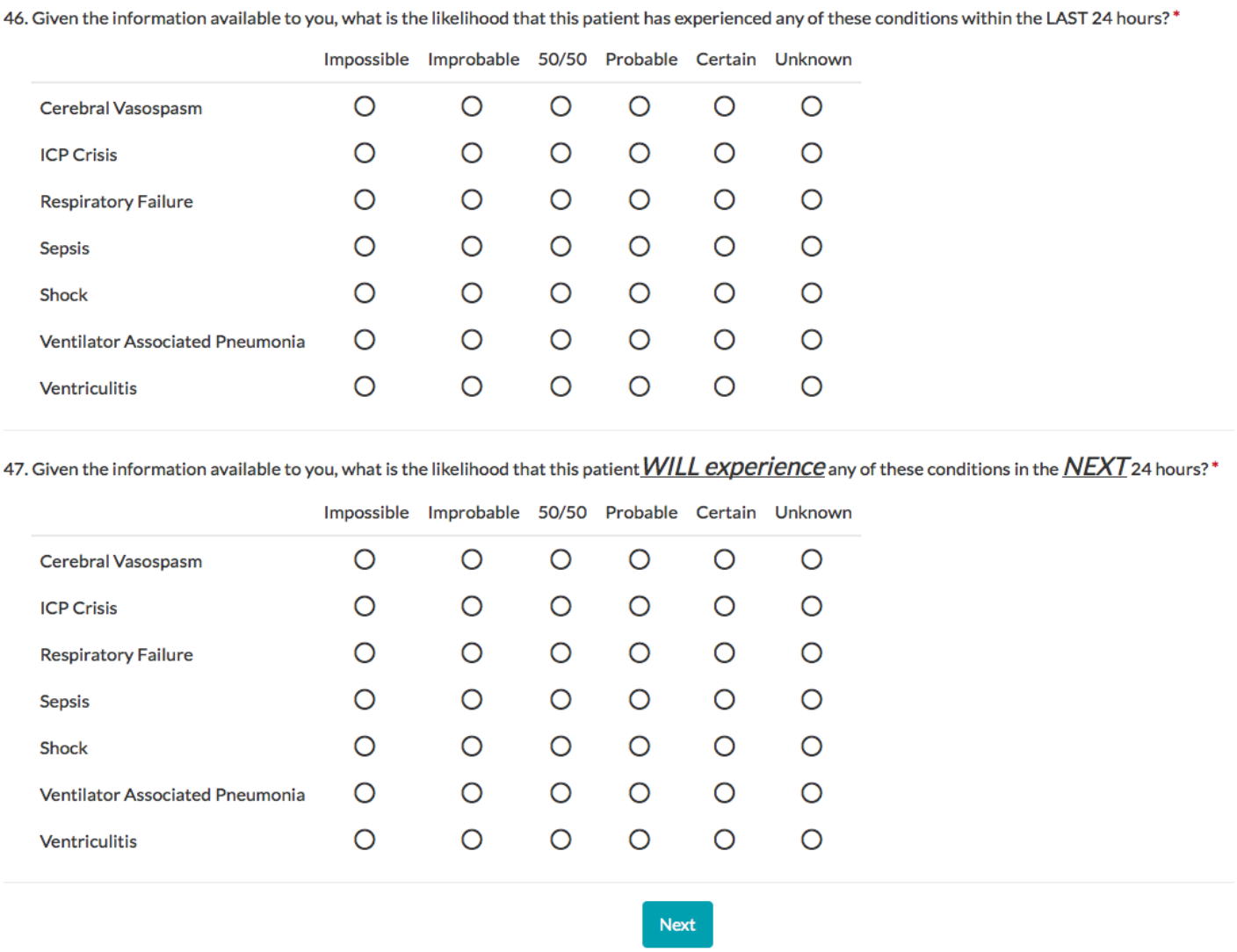
43. How has the patient CHANGED during the time period shown (i.e. has the physiology gotten better or worse during the day)? *

| | Much Improved | Improved | No Change | Worse | Much Worse | Unavailable/Unknown |
|---|---|---|---|---|---|---|
| Patient Status | ○ | ○ | ○ | ○ | ○ | ○ |

44. Which tests (if any) would you order for this patient based on the information provided? *

45. Are there any therapeutics that you would order? *

Figure 20. Likelihood of clinical events in last 24 hours and next 24 hours



46. Given the information available to you, what is the likelihood that this patient has experienced any of these conditions within the LAST 24 hours? *

| | Impossible | Improbable | 50/50 | Probable | Certain | Unknown |
|---|---|---|---|---|---|---|
| Cerebral Vasospasm | ○ | ○ | ○ | ○ | ○ | ○ |
| ICP Crisis | ○ | ○ | ○ | ○ | ○ | ○ |
| Respiratory Failure | ○ | ○ | ○ | ○ | ○ | ○ |
| Sepsis | ○ | ○ | ○ | ○ | ○ | ○ |
| Shock | ○ | ○ | ○ | ○ | ○ | ○ |
| Ventilator Associated Pneumonia | ○ | ○ | ○ | ○ | ○ | ○ |
| Ventriculitis | ○ | ○ | ○ | ○ | ○ | ○ |

47. Given the information available to you, what is the likelihood that this patient *WILL experience* any of these conditions in the *NEXT* 24 hours? *

| | Impossible | Improbable | 50/50 | Probable | Certain | Unknown |
|---|---|---|---|---|---|---|
| Cerebral Vasospasm | ○ | ○ | ○ | ○ | ○ | ○ |
| ICP Crisis | ○ | ○ | ○ | ○ | ○ | ○ |
| Respiratory Failure | ○ | ○ | ○ | ○ | ○ | ○ |
| Sepsis | ○ | ○ | ○ | ○ | ○ | ○ |
| Shock | ○ | ○ | ○ | ○ | ○ | ○ |
| Ventilator Associated Pneumonia | ○ | ○ | ○ | ○ | ○ | ○ |
| Ventriculitis | ○ | ○ | ○ | ○ | ○ | ○ |

Next

## *REMAINING WORK AND CHALLENGES*

Conducting the cognitive experiment, analysis of its data, and reporting upon the results is the remaining work to be completed. Data collection is in progress and will 6-10 weeks to complete. The project continues to move forward, though more slowly than anticipated, and will be completed without the need for additional funding.

## *FUTURE PLANS*

Results from the cognitive experiment will provide feedback needed to refine the visualization tools that we have developed. In our cognitive work analysis we also identified a need for a patient visualization that provides an overview of all critical systems for the patient, including labs and medications. The workflow progression would be to use the overview visualization developed in this proposal to identify which patient needs to be evaluated. The next visualization would then provide a broad overview for an individual patient, including elements that have been developed in this proposal, as well as additional elements that help the clinician identify clinical events and alarm status, the physiologic state of organ systems including labs, and current medications. The clinicians would identify areas of concern and could then drill down into the sepsis or ICP management visualizations to facilitate a specific treatment decision.

Additionally, we have begun to create multiple mockups for other interactive visual support tools to help clinicians with other cognitive and collaborative challenges (See uploaded powerpoint presentation). We have also connected our web-based tool to a real-time data feed, but there are limitations to this approach in terms of how much information a web browser can hold without experiencing slowdown. There is a need to study more intensively what the right combination of static and live data should be used to support visualization applications. These ideas are worthy of further study and as such our proposed plans for next steps include:

**Aim #1: Refine the current prototype** – Based on our experiment results the first step would be to further refine the designs and add a new patient-specific summary page. We have included a powerpoint presentation (Appendix A) with mockups that expand on many of these ideas.

**Aim #2: Transition the current prototype to real-time system** – This would involve data model development to ensure the appropriate data syntax and semantics are represented for the real-time PREDICT system. Then the IMEDS middleware would be implemented to provide the appropriate services while the IMEDS API is developed to support the PREDICT system requirements and ICE compliance.

**Aim #3: Deploy PREDICT system to Columbia, Emory, and UCLA** – Expanding to include three different institutions is critical to understanding generalized and specific clinician needs and IT design. Quantitatively assessing how these differences affect the innovative decision support tool and clinical benefits (related to patient outcomes) is important for future adoption by other clinical environments.

**Aim #4: Evaluate PREDICT system at three sites to determine impact on results of patient outcomes and paths to those outcomes** – An evaluation including a structured survey of clinicians' experience in ease of data acquisition, quality of decision-making, and time saved (or wasted), and patients' clinical outcomes.

# KEY RESEARCH ACCOMPLISHMENTS

- Devised methods to both filter and interpolate physiological data.
- Created physiologic indices for clinically meaningful variation among several parameters using a version of empirical orthogonal functions.
- Applied the above physiologic indices to create a patient overview visualization to help clinicians identify patients that are changing and inserted these indices into the sepsis specific decision support visualization.
- Created a sepsis identification visualization tool to help clinicians identify patients headed for septic shock.
- Generated a visualization tool to help clinicians assess intracranial pressure and generate patient specific physiologic set-points for goal directed therapy.
- Demonstrate a real-time data feed to a visualization tool that contains elements from each of the three prototype visualizations.

# REPORTABLE OUTCOMES

- Schmidt, J. M., Irvine, J. M., & Miller, S. (in press). Data Visualization. In M. DeGeorgia & K. Loparo (Eds.), *Neurocritical Care Informatics: Translating Data into Bedside Action*: Springer.
- Schmidt, J. M., Doerner, J., Sow, D., Perotte, A., & Mayer, S. *BEDSIDE APPLICATION FOR THE ASSESSMENT OF CEREBRAL AUTOREGULATION AND PATIENT STATE CHANGES*. Neurocritical Care*,* 2013. *19*, S205.
- Schmidt, J. M. (2013, November). *Streaming Analytics Case Study in Columbia University Neuro-ICU* Paper presented at the EME Streaming Analytics Symposium, Chicago, Illinois.

# CONCLUSION

In the intensive care unit environment clinicians are under a constant state of information overload. Patients in need to medical attention are not identified in a time to treat them beneficially, and mismanagement from a lack of understanding of patient occurs too frequently. These problems lead to lower quality patient care resulting in more secondary complications, less than optimal outcomes for patients, and longer ICU length of stay increasing healthcare costs. Results from our cognitive work analysis confirmed the need for improvements in patient information presentation to facilitate clinical decision making. We identified the need for a patient overview screen that contains data from bedside monitors, electronic health record, and laboratory systems. This type of visualization was not within the original scope of work and remains an important unmet need. The three visualization prototypes that we did develop are meant to help clinicians on a variety of important clinical tasks including: 1) prioritizing patients most in need of medical attention, 2) identifying patients at high risk for sepsis, and 3) managing intracranial pressure crises and identifying patient specific physiologic targets. A cognitive experiment will be conducted in the next period to determine what works and what does not work regarding our visualization designs; this will allow firmer conclusions to be drawn and will support the next phase of development for medical data visualization and decision support in the intensive care unit environment.

Several steps need to be completed to move towards a deployable clinical decision support tool. A new phase of visualization development is needed informed by the findings of the cognitive experiment. Over the last year, each visualization evolved substantially and this process should continue. The visualization tools need to optimized for real-time deployment, either fed by a real-time data stream as we have demonstrated here or fed from a real-time file structure. Deploying and evaluating the visualization tools to multiple sites is a crucial step in this development. This will provide a framework for general deployment and provide an opportunity to evaluate these designs clinically to determine if in fact decision support tools improve clinician decision making resulting in less secondary complications, shorter ICU length of stay, and improvements in long-term outcome.

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# APPENDICES

- Powerpoint presentation containing mockup visualizations for future work.


HOME
DETAILED STATUS
MONITORING
ALARMS
Patient
Autoregulation
Sepsis
TIME
NOW
+6h
+12h
+18h
+24h
NOW
+6h
+12h
+18h
+24h
Doe, E.
Dove, J.
Johnson, P
Myers, S.
Palli, H.
Ryan, R.
Ven, O.
Zanelli, U.


HOME
DETAILED STATUS
MONITORING
ALARMS
Doe, E
Wen, O
Doe, Joe
Dove, J
Johnson, P.
Myers, S
Palli, H.
Doe, Jane
ID: 569402
DOB: 1965/02/21
Zoom:
1h
2h
6h
8h
12h
24h
1w
ALL
Physiological
Sepsis
WBC
Temp
HR
Resp
Meds
Saline (3%)
Mannitol
2011
2012
Labs
WBC
Platelet
Creatinine
Lactic Acid
AST
SuperAlarm
Red
Asystole
VFIB/VTAC
Apnea
V Tach
12-16
2-29
2-29
11


HOME
DETAILED STATUS
MONITORING
ALARMS
Cerebral Profusion
ICP Trending
Sepsis Trend
PbtO2 (mm Hg)
Cerebral perfusion pressure (mm Hg)
80
128
Set Goals
ICP
MAP
CPP
PBtO2
Mannitol


HOME
DETAILED STATUS
MONITORING
ALARMS
Cerebral Profusion
Cerebral perfusion pressure (mm Hg)
ICP Trending
Sepsis Trend
75
50
25
50 75 100 125 150 175
Physiological
ICP
MAP
CPP
PBCO2
Medications
Mannitol
80
60
40
Labs
Serum Osmolality
Serum Sodium
Urine Osmolality
Urine Sodium
ABG PO2, PCO2


HOME
DETAILED STATUS
MONITORING
ALARMS
Cerebral Profusion
ICP Trending
Sepsis Trend
Cerebral perfusion pressure (mm Hg)
75
50
25
100
125
150
175
Physiological
ICP
MAP
CPP
PBCO2
Medications
Mannitol
80
60
40
Labs
Serum Osmolality
Serum Sodium
Urine Osmolaity
Urine Sodium
ABG PO2, PCO2


HOME
DETAILED STATUS
MONITORING
ALARMS
Cerebral Profusion
Cerebral perfusion pressure (mm Hg)
ICP Trending
Sepsis Trend
BP
TEMP
HR
WBC
HRV
RR
-00:30:00
00:00:00
+00:30:00
Timeline : Patient : Term
Physiological
ICP
MAP
CPP
PBCO2
Medications
Mannitol
80
60
40
Labs
Serum Osmolality
Serum Sodium
Urine Osmolaity
Urine Sodium
ABG PO2, PCO2


HOME
DETAILED STATUS
MONITORING
ALARMS
Zoom: 1h 2h 6h 12h 1D 1W All
Current Setting
Mon Sep 10
11 am
12 pm
1 pm
Last 1 h
Last 12 h
Last 24 h
SuperAlarm
Crisis
Asystole 12-16
VFIB/VTAC 2-29
Apnea 2-29
V Tach 11
Warning
VT>2
V Brady
Pause
Tachy
Irregular
No breath
Brady
Device
R on T
Trigeminy
Bigeminy
PVC
ACC vent
Artifact
CAL CO2
Check Adapter
Cal Censor
Monitor
Leads fail
RR leads fail
No Telem
Techical/System
Physio
HR
SPO2
ART
CVP
ICP