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: October 2015

TYPE OF REPORT: Final

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
October 2015	Final	1Feb2013 - 31Jul2015

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

6. AUTHOR(S)
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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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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
Nothing listed

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			USAMRMC
U	U	U	UU	36	19b. TELEPHONE NUMBER *(include area code)*

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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.

KEYWORDS

KEYWORDS: data visualization; data reduction; linear projections; clinical decision making; intensive care; physiological data; sepsis

ACCOMPLISHMENTS

What were the major goals of the project?

Milestone 1: Prototype visualization development complete
Duration: 3 months (Month 1-3)
Percentage of Completion: 100%

Milestone 2: Data collection, analysis, and deployment to back-end data system complete
Duration: 6 months (Month 4-9)
Percentage of Completion: 100%

Milestone 3: Interactive visual interface complete and connected with the data
Duration: 6 months (Month 4-9)
Percentage of Completion: 100%

Milestone 4: Conduct Cognitive Experiment to evaluate visualization tool
Duration: 3 months (Month 9-12)
Percentage of Completion: 100%

What was accomplished under these goals?

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.

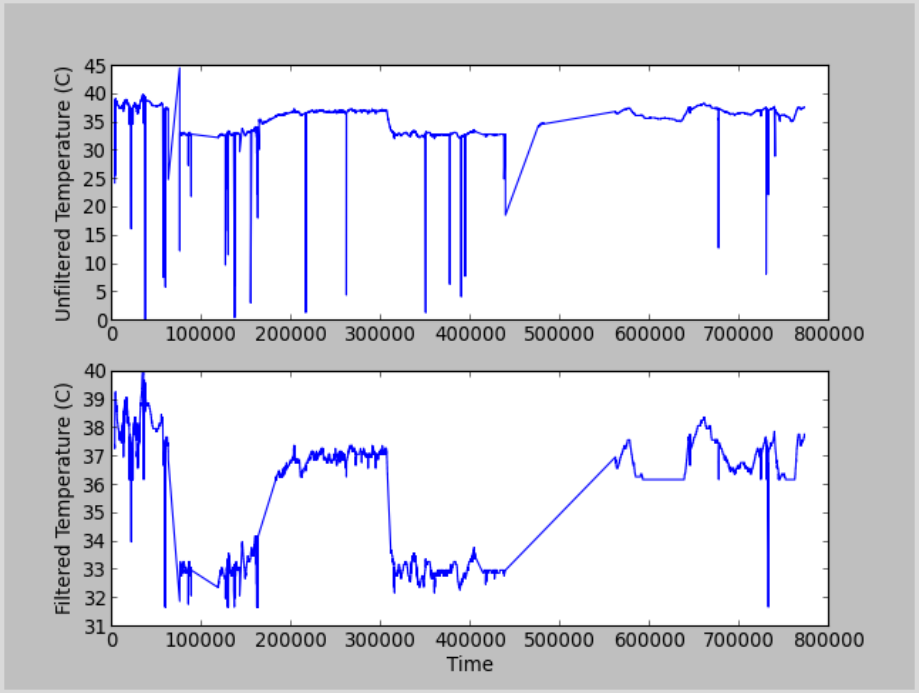
Draper Laboratory human-factor engineers gained a comprehensive understanding of the needs and data requirements for the three case scenarios by completing (3/15/13) a cognitive work analysis (CWA) with clinical staff from the Columbia University Neurological Intensive Care Unit. Columbia University 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.

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



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.

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

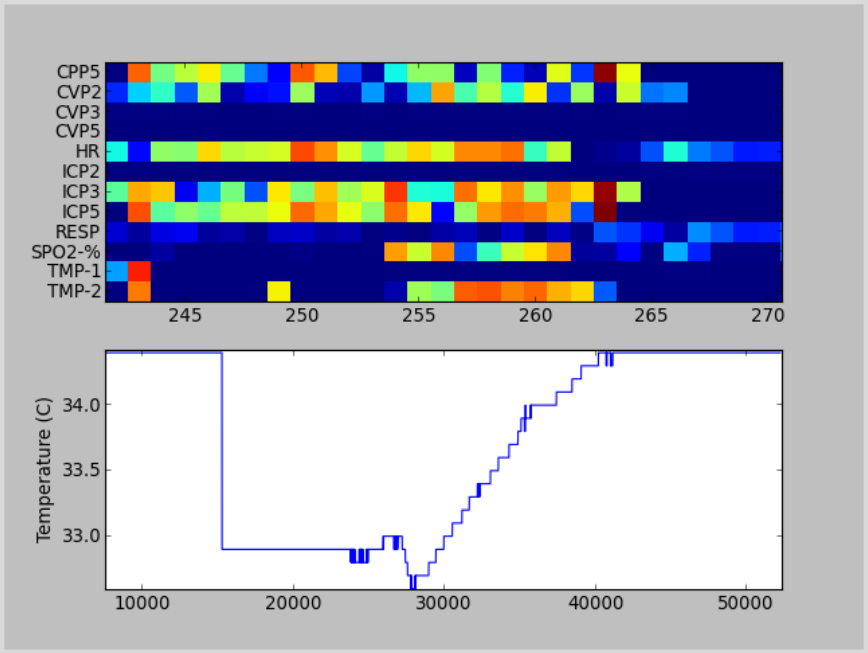
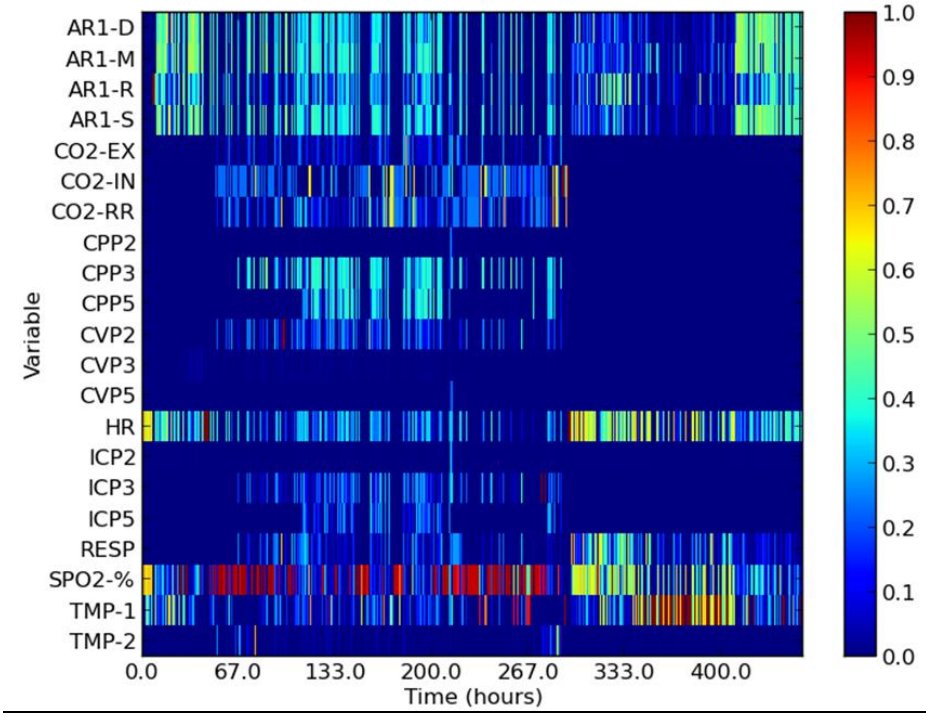


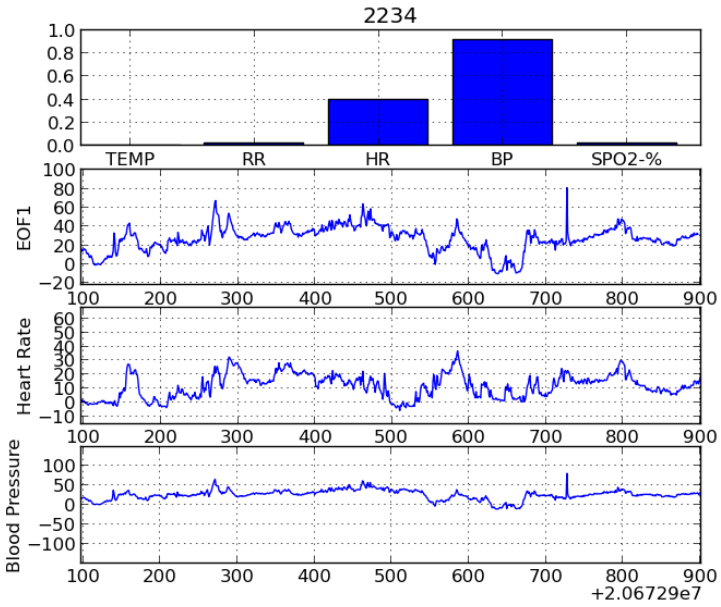
Figure 3. EOF Analysis Results for Individual Patient



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.

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 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 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

Figure 4. EOF Composite Score for Individual Patient

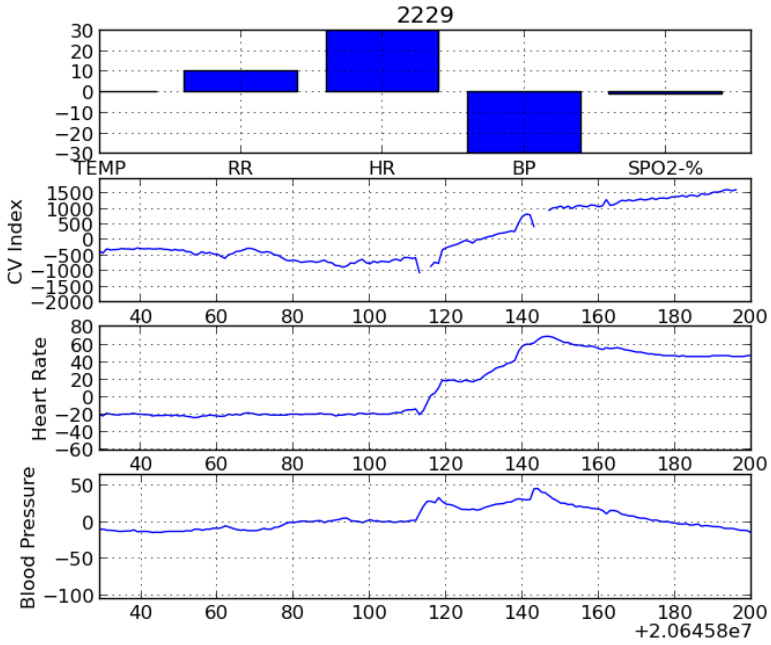


From top to bottom: The variable weightings for the first EOF, the projection of the first EOF onto patient 2234's multivariate time series, patient 2234's heart rate time series and patient 2234's blood pressure time series.

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
patients. The initial method we outlined evaluates a similar 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 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.

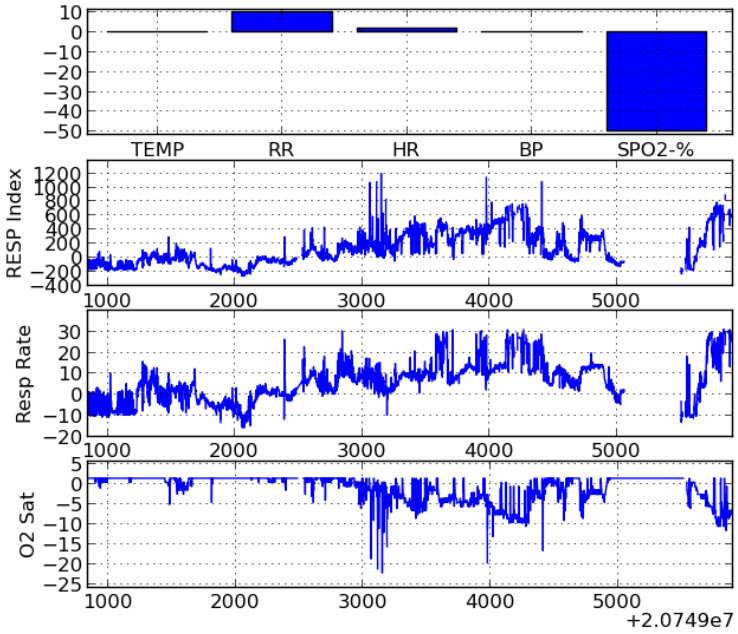


Figure 5b. A pre-specified weighting corresponding to respiratory distress that is demonstrated during a portion of patient 2247's time series. From top to bottom: The respiratory distress variable weightings, the projection of the weightings onto the multivariate patient time series to create the Resp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

Figure 6. EOF Composite Score Overview Format

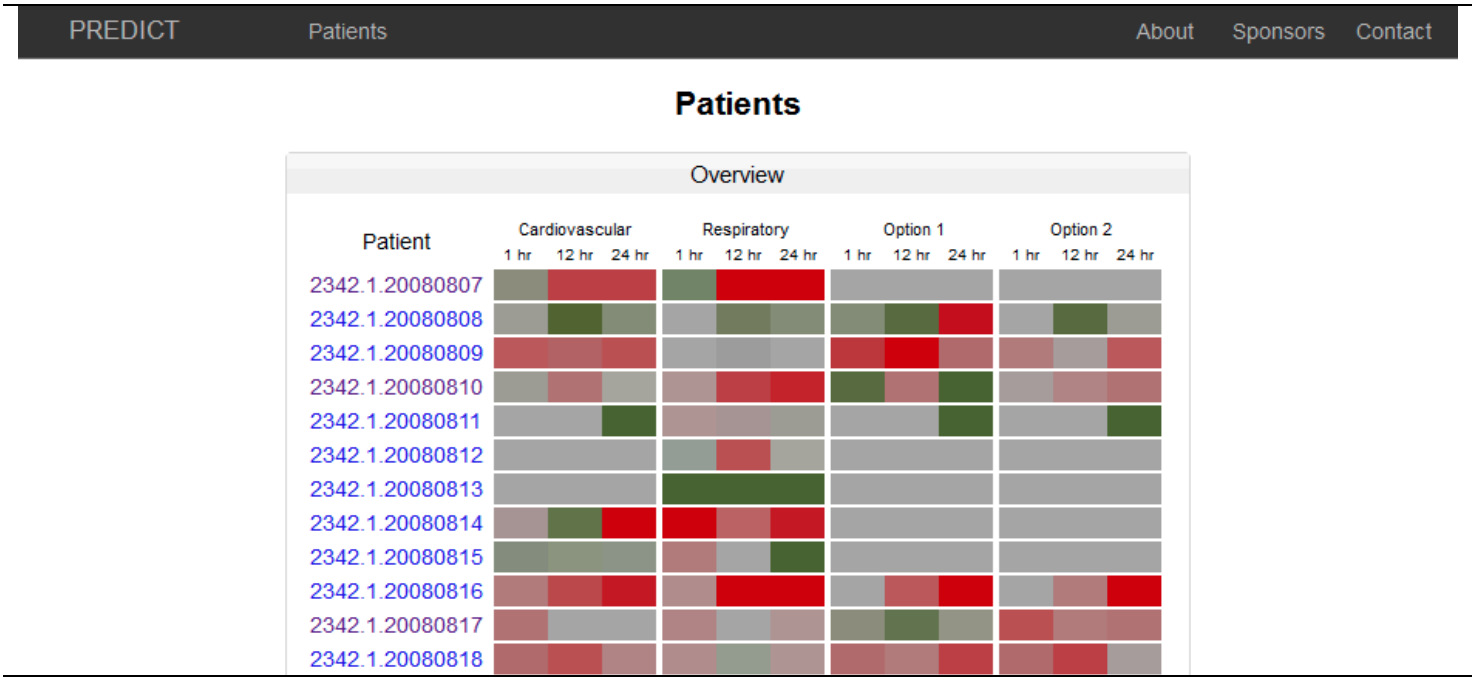


Figure 6. The patient overview page provides clinicians 1 hour, 12 hour, and 24 hour windows for change on two pre-specified and two unspecified EOF clinical indices. We will test in a cognitive experiment whether clinicians are able to identify patients that need attention first using this approach.

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):

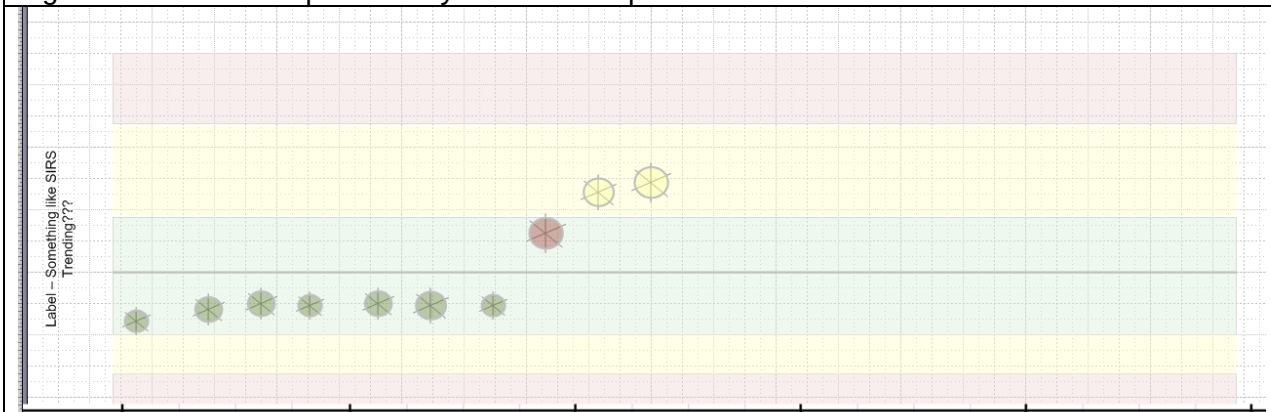
1) temperature
2) heart rate
3) respiratory rate
4) white blood cell count
5) heart rate variability
6) blood pressure

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																				

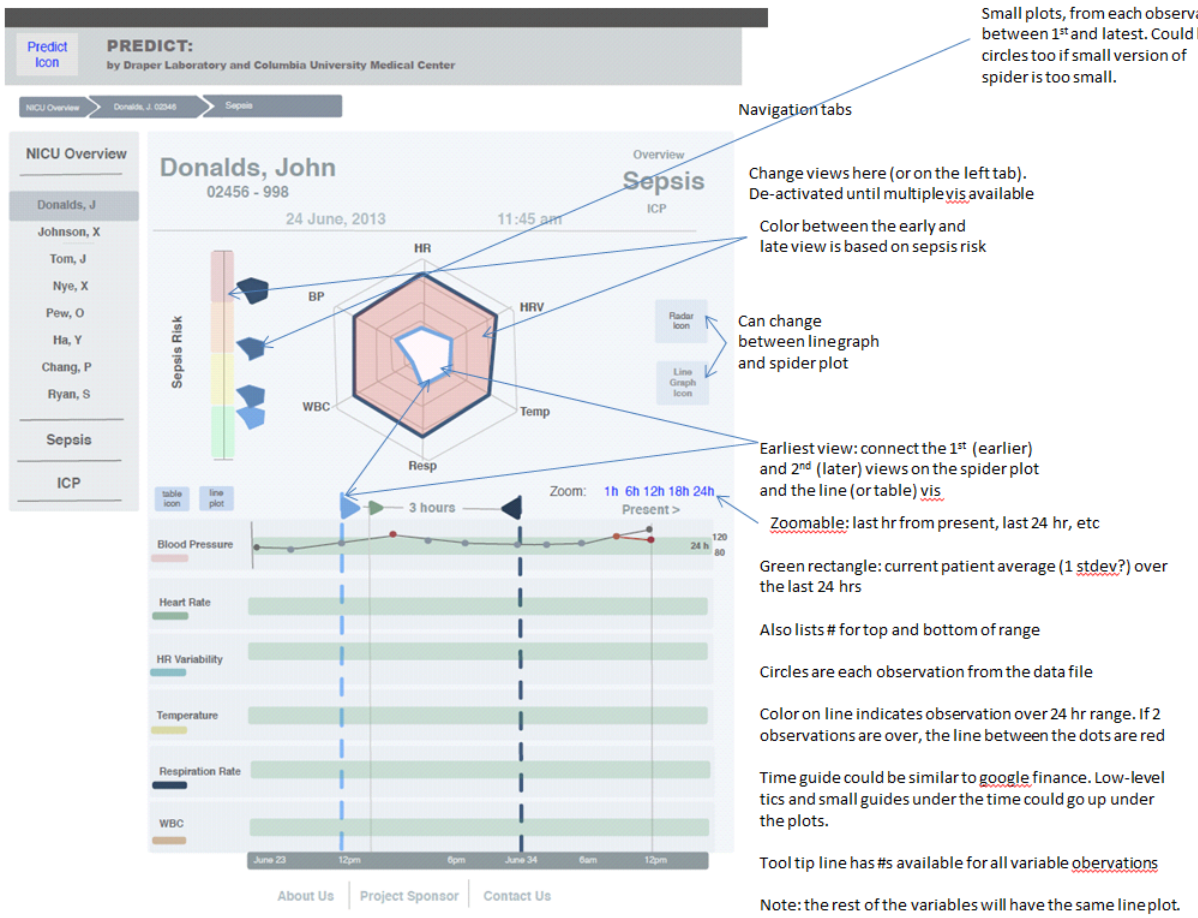
In the initial mockup the circle (Figure 7) was not actually meant to be read (no individual variables or numbers). We believed that showing an increasing size (and color and position) could be used to easily indicate to clinicians that SIRS is emerging. The clinician or nurse can then dig deeper into 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.

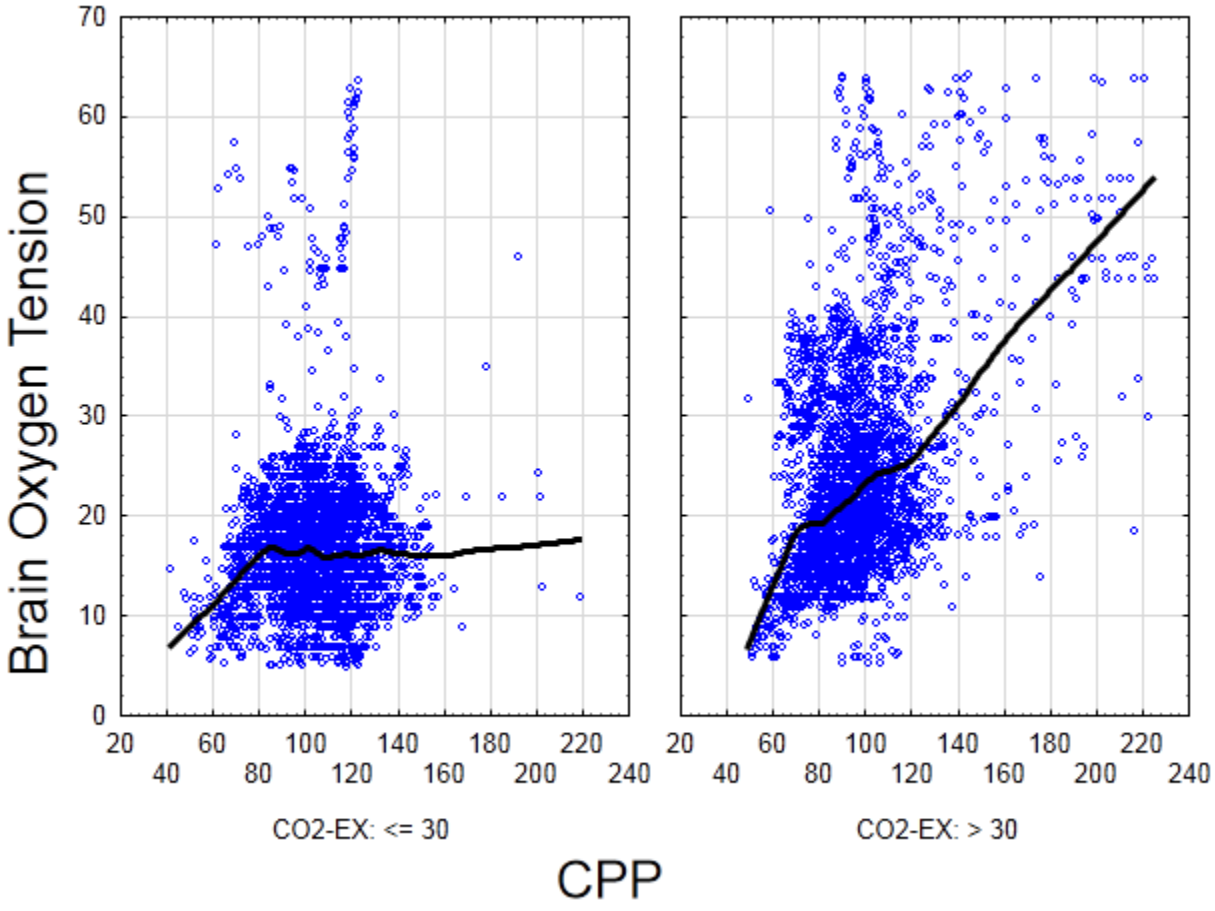
Figure 9. Sepsis Visualization Tool

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

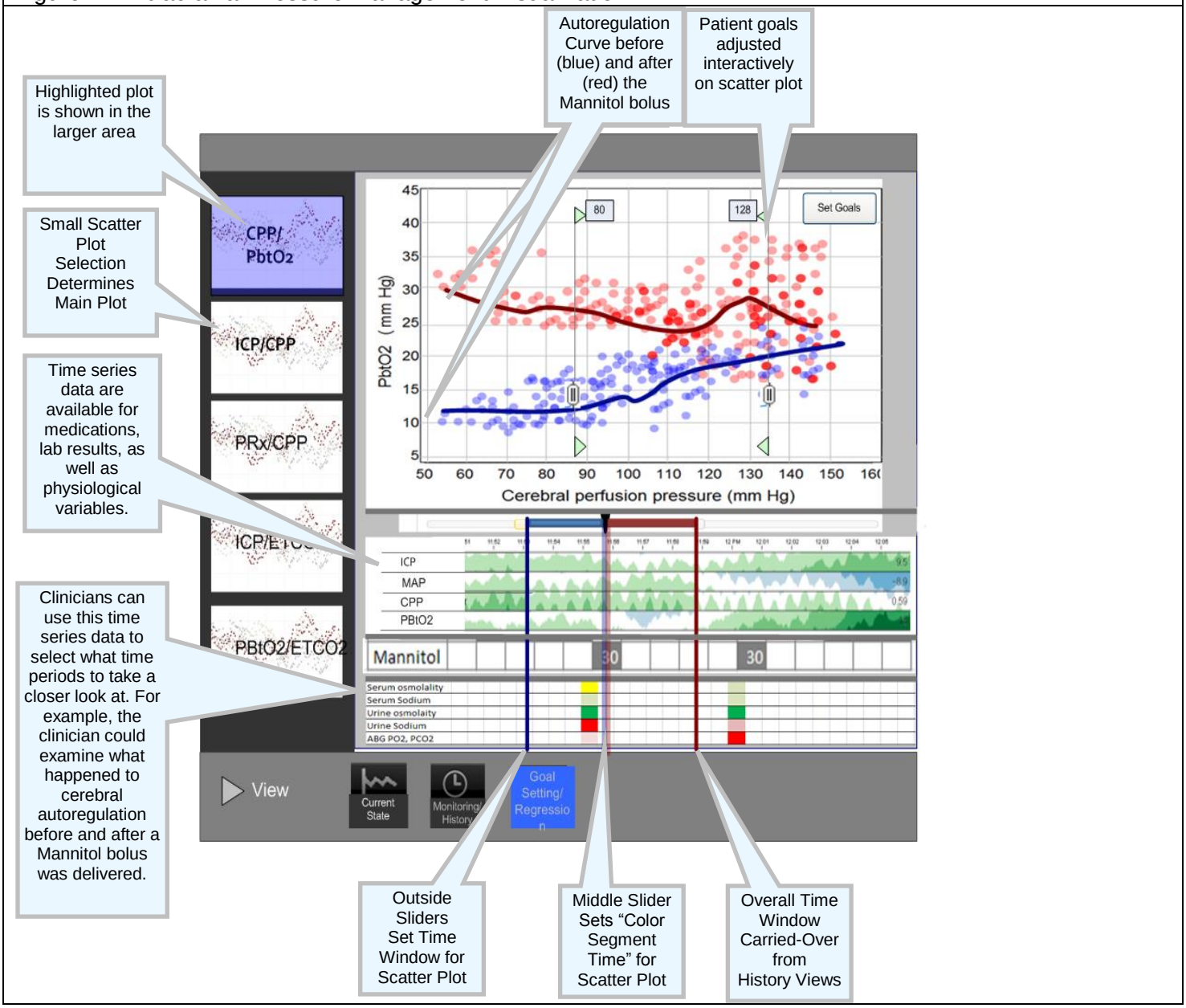
The goal and purpose of the intracranial pressure management interactive visualization is to determine an 'ideal' target for cerebral perfusion pressure that will maintain adequate perfusion of the brain. The clinical task is to determine an 'ideal' target for cerebral perfusion pressure that will maintain 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.

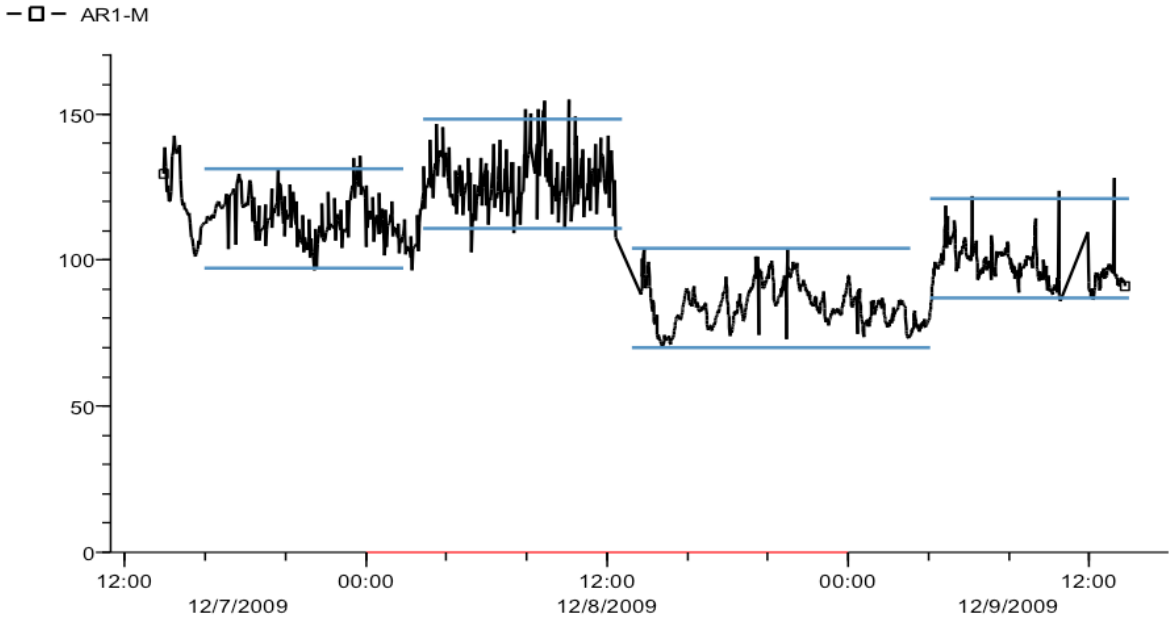
Figure 11. Intracranial Pressure Management Visualization



Real-time visualization demonstration

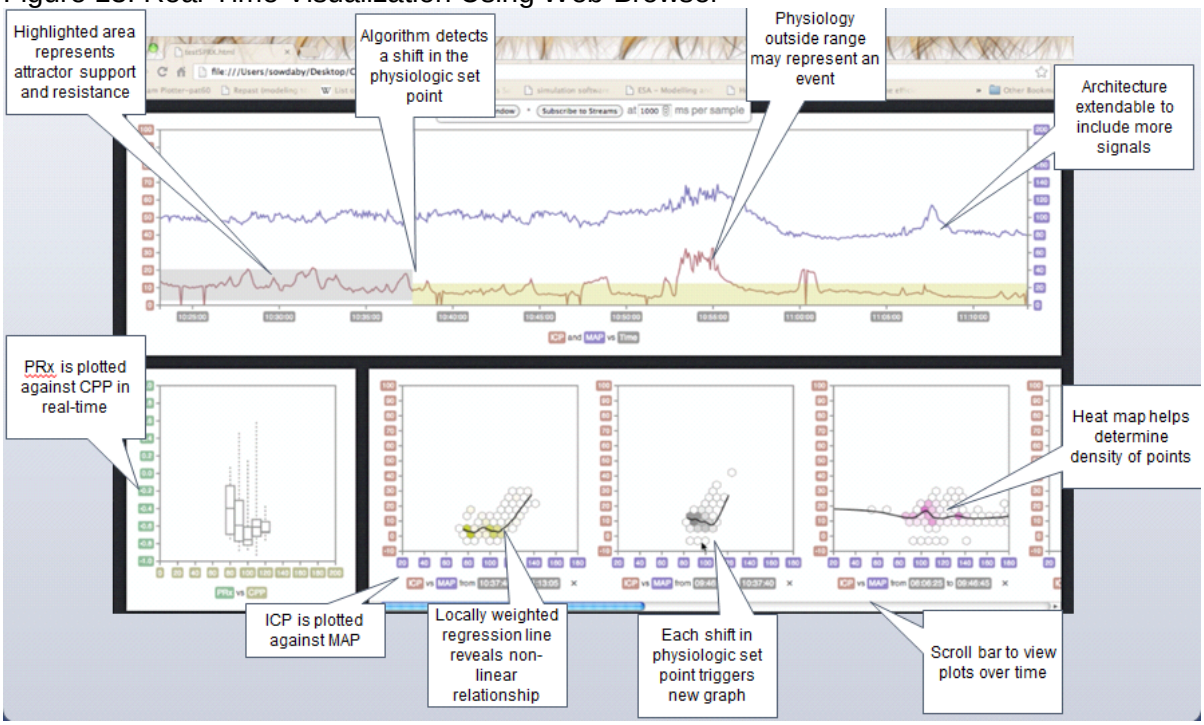
We have started to develop a working real-time demo that incorporates the principles of the three visualizations. Chaos theory describes the behavior of attractors in dynamical systems such as in human physiology. In practice physiology varies around a physiologic set point until the system is perturbed 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



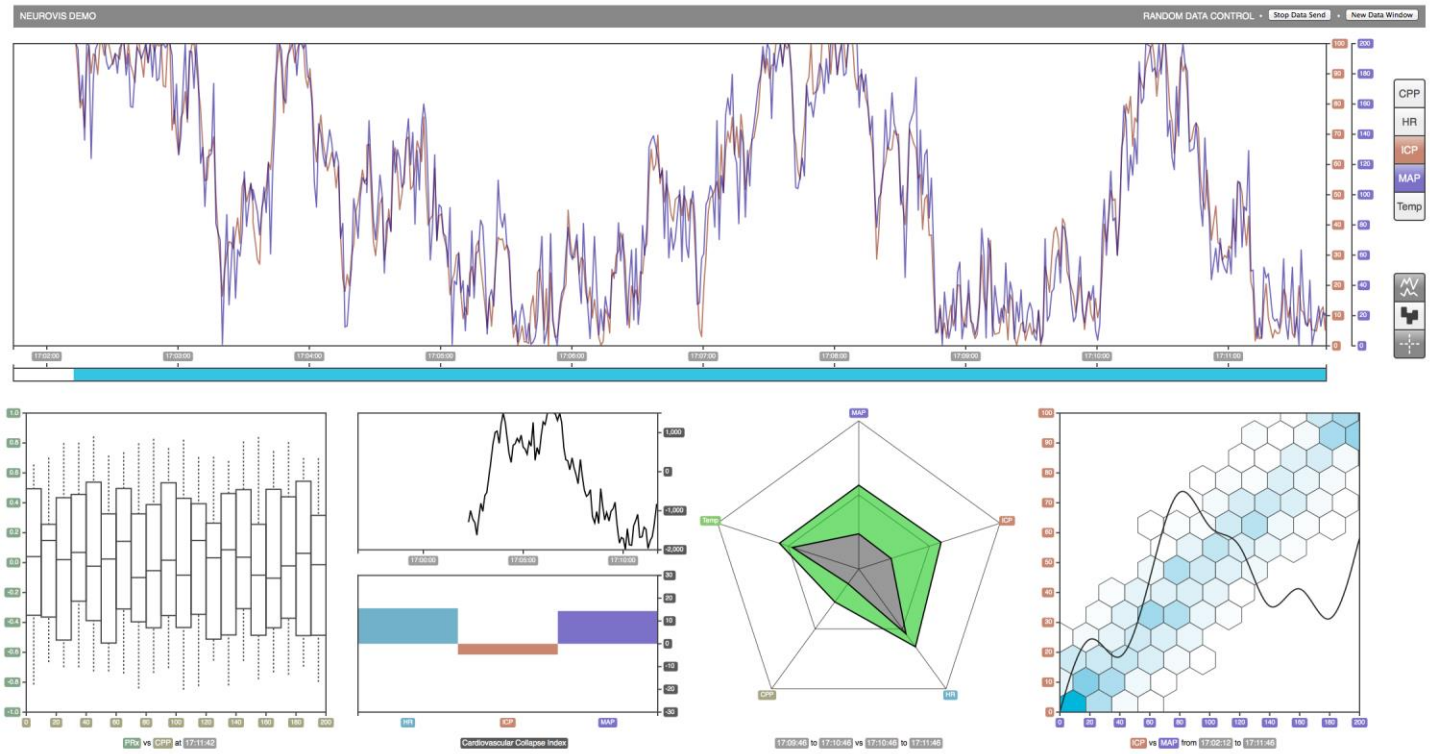
Assessment of cerebral autoregulation using the pressure reactivity index (PRx) is a common application of multimodal neuromonitoring data. We have developed a demonstration real-time web application to enable clinicians to assess cerebral autoregulation status and identify potential patient state changes 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 4 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 Appendix 1-5.

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

Subjects were also presented an EOF composite score visualization composed of 28 patients (See Appendix 6) and asked to create a list the 3 patients that they would round on first, and 3 patients they would round on last. The EOF composite score represents the variation or change a patient has experienced in the last 1, 12, and 24 hours in the cardiovascular and respiratory domains. It also displays variation within 2 undefined domains and would represent any change. Orange represents clinically significant variation. For example in the cardiovascular domain orange represents that heart rate has increased while blood pressure has fallen. Blue reflects the opposite change – heart rate decreasing while blood pressure increases. This too could represent a clinically meaningful change, but it is less often considered life threatening.

Results

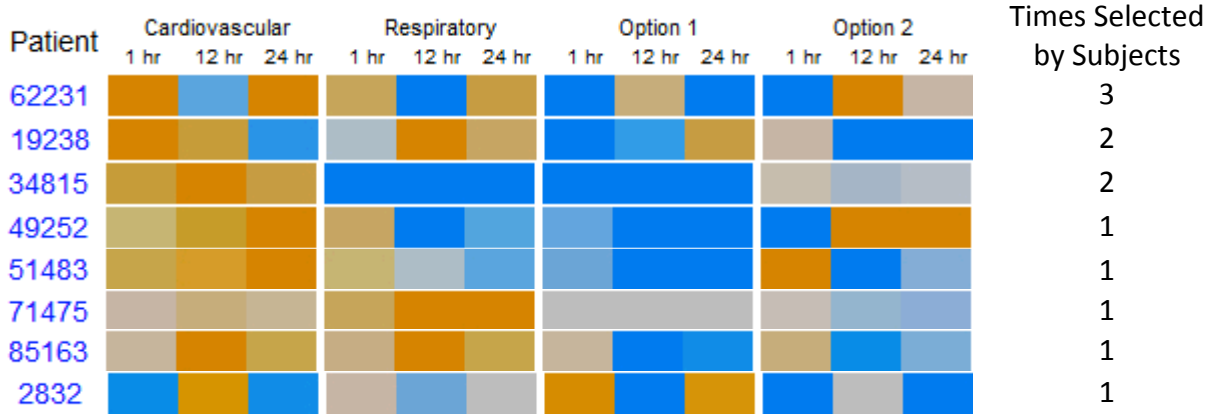
EOF composite score overview visualization

Subjects were asked to select 3 patients out of 28 to round on first as well as 3 patients to round on last. Four clinicians (subjects) completed the experiment. The average time to complete the task was 4.4 minutes.

Three patients to round on first:
Subjects reported a similar rationale for these choices, which were the following:

1. CV index worsening on the first two codes, and stably poor on the third one over the past 24 hrs.
2. All of these patients seem to have worsening of cardiopulmonary status in the past 24 hours in descending order of severity.
3. Have had negative trends in the last hour
4. seem to be changing the most in the last hour

Table 2. Selected Patients to Round on First



Times Selected by Subjects
3
2
2
1
1
1
1
1

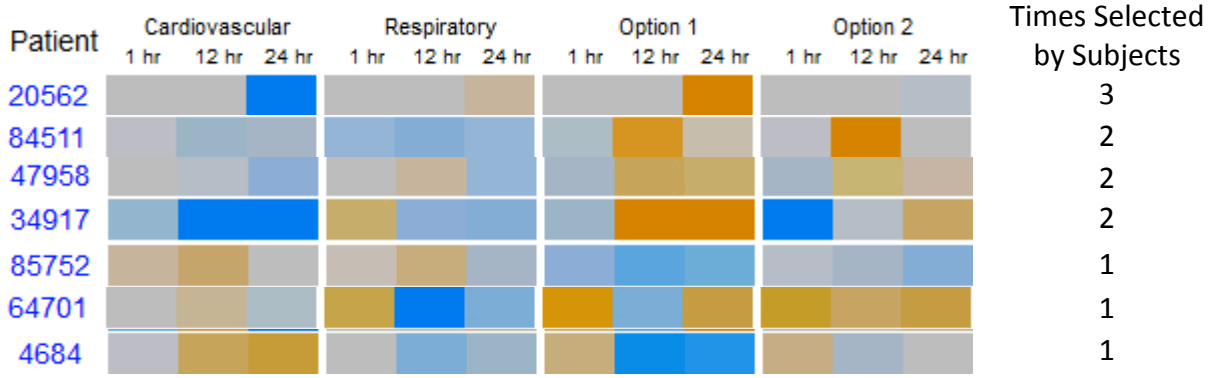
A standard balls and urn calculation suggests that the likelihood of 2 subjects selecting the same patient is 0.007 compared to a likelihood of 0.12 of any subject selecting any 1 patient from the list of 28. The likelihood of 3 subjects selecting the same patient is 0.0002.

The stated rationale for the patient selection by subjects stressed cardiopulmonary difficulty over respiratory distress, which is reflected in the choices by the subjects. For these patients select by more than one subject, two had the darkest orange (most change) in the cardiopulmonary index over the last hour (62231, 19238) and the other (34815) contained the most orange in total over all three time periods. Patient 2832 had the darkest blue in the last hour of all patients in the cardiopulmonary index. Patient 49252 and 51483 had the darkest orange in the last 24 hours of all patients in the cardiopulmonary index. Patient 85163 had the darkest orange in the 12 hour time period for both cardiopulmonary and respiratory indices, while patient 71475 had the most orange across all time periods in the respiratory index.

Three patients to round on last:
Subjects reported a similar rationale for these choices, which were the following:

1. CV and RESP indices look stable to better; not sure how to incorporate the option 1/2 indices though none of these are orange in the past hr. All three seem either stable or improving (i.e. more blue/grey than orange).
2. These patients all appear roughly stable with less change. Even though 4684 has possibly slight worsening in CI, respiratory status is better and the other variables do not seem to have changed much.
3. These patients have been stable to improving
4. Least change over 24 hrs.

Table 3. Selected Patients to Round on Last



Times Selected by Subjects
3
2
2
2
1
1
1

A standard balls and urn calculation suggests that the likelihood of 2 subjects selecting the same patient is 0.007 compared to a likelihood of 0.12 of any subject selecting any 1 patient from the list of 28. The likelihood of 3 subjects selecting the same patient is 0.0002.

Subjects again appeared to choice patients consistent with their stated rationale. None of the subjects had strong change (orange or blue) in the last hour, and none had strong orange at any point in the cardiovascular or respiratory domains.

These data suggest that color coding patients allowed clinicians to discriminate stable from unstable patients quickly. Additional study is required to determine whether detecting physiologic 'change' provides clinicians essential information they need about patients, or what kind of metrics might best discriminate patients that need attention.

Importantly what this data suggest is that the strategy employed whereby data is automatically processed for clinicians in some meaningful way and presented in an easily understandable format enabled clinicians to easily and reliably discriminate patients that need attention from those that do not. This strategy appears to provide users immediate situational awareness about the status of the patient.

Visualization versus text for physiologic and clinical event detection

Time to Complete. Four subjects completed the experiment, taking an average of 4.5 hours to complete. The average (standard deviation) time to complete a case in the text condition was 290 (122) seconds, which was significantly less than the 402 (204) seconds subjects required to complete the visualization condition ($T_{(69)}$ = 4.636, P<001).

The text condition was designed to be similar to clinical conditions in the ICU. The rate of physiologic data was one value every hour whereas for the visualization condition data was presented once every minute. Our data suggest that presenting more raw data, even in visual form, increases the time it takes clinicians to process that data.

Physiologic Event Detection. Subjects were asked to identify the number of physiologic events that occurred during the last 24 hours and also determine whether the patient has gotten better or worse in that time. The average weighted Cohen's Kappa of the four subjects was not significantly different for any event. **This data suggests that clinician judgments regarding the occurrence of physiologic events did not differ depending on whether data was presented in text or visual form (Table 4).**

Clinical Event Detection. Subjects were asked what clinical diagnoses they believed were present in the last 24 hours and what events would likely occur in the next 24 hours. Data was analyzed with the nonparametric Wilcoxon rank sum test with continuity correction using a p-value threshold of 0.01 to determine statistical significance. **There was no evidence to suggest that raw data presented in visual form provide clinicians additional situational awareness or increased certainty regarding the presentation of clinical complications (Table 5).**

Table 4: Clinician Agreement on Occurrence of Physiologic Events

	Average Weighted Cohen's Kappa			
Clinical Events	Text Condition	Visual Condition	T-Score	P-Value
Overall	0.25	0.27	-0.38	0.71
Bradycardia	0.30	0.28	0.14	0.89
Fever	0.32	0.34	-0.06	0.95
Hypothermia	0.34	0.36	-0.07	0.94
Hyperventilation	0.10	0.13	-0.15	0.88
Hypoxia	0.23	0.22	0.06	0.96
Hypertension	-0.02	0.21	-1.2	0.26
Hypotension	0.35	0.40	-0.19	0.85
ICP elevation	0.34	0.24	0.46	0.65

Table 5: Clinician Certainty of Clinical Complications

Clinical Events	Control Cases	Event Cases	Wilcox W	P-Value
Sepsis (Last 24 hours)				
Text	2 (2, 3)	2 (2, 3)	515	0.41
Visualization	2 (2, 3)	2.25 (2, 3)	492	0.13
Text - Visual	0 (-0.5, 1)	0 (-1, 0)	623	0.41
Sepsis (Next 24 hours)				
Text	3 (2, 3)	3 (2, 3.75)	410	0.03
Visualization	3 (2, 3)	3 (2, 3.5)	539	0.36
Text - Visual	0 (-1, 0)	0 (-0.5, 0.25)	479	0.27
Respiratory Failure (Last 24 hours)				
Text	3 (2, 4)	3 (2, 4)	527	0.77
Visualization	3 (2, 4)	3 (2, 4.5)	478	0.43
Text – Visual	0 (-1, 1)	0 (-1, 0)	559	0.38
ICP Crisis (Next 24 hours)				
Text	3 (2, 4)	3 (1, 4)	551	0.55
Visualization	3 (2.5, 4)	3.5 (3, 4)	451	0.24
Text - Visual	0 (-1, 1)	0 (-1, 0)	577	0.26

Ratings: 0 = 'Impossible'; 1 = 'Improbable'; 2 = '50/50'; 3 = 'Probable'; 4 = 'Certain'

Discussion

Although the conducted study is limited by the small number of clinicians tested, it does appear to illuminate a number of issues. Contrary to our hypothesis, it our clinicians took longer to process and make decisions about patients in the visualization conduction. Raw data was presented at a higher frequency in the visualization (1 data point / minute) over text (1 data point / 15 minutes) condition. It is possible that clinicians are more practiced at synthesizing text information, however it seems most likely that have more data increased the time clinicians needed to determine how long a patient experienced different physiologic events. This interpretation is consistent with findings from other studies. (9-12)

There was also no evidence to suggest that simply providing raw data in a visual form improved the identification of physiologic events, or improved the clinical recognition of clinical complications, that would warrant providing clinicians higher resolution *raw* data. We did not find any meaningful differences between the text and visualization conditions to suggest that the absence of findings is due to insufficient statistical power. Together this suggests that presenting more data increases clinicians' cognitive load even if data is presented visually, and that simply presenting such data in visual format alone does not reduce clinician cognitive load. In contrast when synthesized data was presented to clinicians (overview visualization) clinicians were able to use reliably to prioritize patients that needed attention and identify patients that were stable.

This finding is in alignment with the idea of automatic processing of information for clinicians can streamline clinical decision making. **Data should be processed for clinicians automatically and results presented in a simple display**. For example, instead of clinicians determining the time patients were tachycardic this

information should be calculated automatically. Clinicians would simply be shown that the patient had been tachycardic for 5 hours in the last 24 hours.

It has been shown that taking information from many screens to one screen improves clinician decision making (11) and it is known that how information is presented influences decisions (13). Data visualization remains important. However our (limited) data do not suggest that providing visual data to clinicians will help them detect subtle changes in physiology that may indicate complex events like sepsis. **A key distinction must be made between visual data representation from decision support.** There are many ways in which data can be visualized to represent knowledge, however representing data visually still requires the user to extract meaning from it. Situational awareness will be most enhanced by automatically extracting information from data and converting that data into information that clinicians can use to make a decision (e.g., risk of a complication, frequency of physiologic events).

Meaningful ways to accomplish data reduction is the biggest barrier to improving clinical decision making. We recommend that future studies focus on methods to reduce the number of data points clinicians must process to obtain situational awareness about patients. The current study explored one possible way to discriminate stable from unstable patients using linear projections of multivariate time series coupled with a simple color-coded scheme. It is unknown if this particular method is a valuable to clinicians, but our data clearly suggest that clinicians were able to quickly and reliably identify patients that were identified by color. A cautionary note is that while color coding based on good underlying information is valuable, color coding based on a poor strategy (e.g., acuity) will be unhelpful or potentially dangerous.

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. This method is generalizable to track any combination of parameters that are deemed clinically important to track.
- 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.

Future Plans

Our cognitive work analysis identified a need for a patient visualization that provides an overview of all critical systems for the patient, including labs and medications. Our cognitive experiment suggests that viable methods to provide clinicians actionable information while reducing the volume of data to synthesize is fundamental to this effort. 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.

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: Development methods of data reduction – conduct observational studies that evaluate the clinical meaning of different mulitivariate linear projections of physiology processes developed in this proposal. Determine what information clinicians use to make specific decisions, and devise methods to generate this information, minimizing or eliminating the need for clinicians to synthesize raw data into actionable information.

Aim #2: Refine the current prototype – Adapt the current prototype to provide synthesized data to clinicians utilizing ecological interface design principles. 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 #3: 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 #4: Deploy and evaluate PREDICT system at three sites (Columbia, Emory, University of Maryland) 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.

Conclusions

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. The visualization tools need to be 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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What opportunities for training and profession development has the project provided?

Nothing to report.

How were the results disseminated to the communities of interest?

Findings from our cognitive work analysis were incorporated into a book chapter regarding data visualization in neurocritical care. Our visualization tools have been presented to thought leaders regarding clinical informatics in the intensive care community in the form of an abstract and two invited talks at an international conference and symposium. The results of the cognitive experiment were recently presented at an international symposium on applications of streaming analytics in critical care. Java code for the real-time visualization has been shared with investigators at Harvard University.

- 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.
- Schmidt, J. M. (2014, August)*. What am I thinking about?* International Conference on Complexity of Acute Illness. Charlottesville, Virginia*.*
- Schmidt, J. M. (2015, September). *Results from Data Visualization Cognitive Experiment.* Paper presented at the EME Streaming Analytics Symposium, Chicago, Illinois.

What do you plan to do during the next reporting period to accomplish the goals?

Nothing to report.

IMPACT

What was the impact on the development of the principal discipline(s) of the project?

This project was impactful primarily in three ways. First we demonstrated the application of a method to reduce multiple related high resolution physiologic parameters to a single that can be tracked over time, used to alert of clinical staff, and used as the basis of a clinical decision support tool that helps clinicians identify patients that are either unstable or have changed in status over a specific time period. Most importantly, this methods overlays clinical knowledge to the data such that physiologic patterns that are known to be dangerous to the patient can be tracked. Second, we had multiple opportunities to convey to the larger research community that it is insufficient to improve clinical decision making by simply presenting raw data in visual form. The field is working to address this in two ways. One is to have dedicated e-icu staff track patient data 24/7 looking for signs of physiologic derangement or imminent clinical events. When potential problems are observed they call the clinicians treating that patients and let them know to go check their patient and give an indication as to their concern. This approach allows nurses in particular to complete their duties without having to constantly look at the data for problems, which is unrealistic and compounded by alarm fatigue. The best example of this are initiatives at Emory University led by Tim Buchman, MD. The second approach has been to continue to develop data reduction methods that extract clinically important information to providers. Instead of providers looking at data and deducing for themselves that there may be a problem, computer algorithms automatically process large volumes of data and providers clinicians a risk assessment for different clinical events. This information can be more easily incorporated into clinical workflow. Lastly, code to generate the visualization tools tested in this project are available to the research community and has already been shared with investigators at Harvard University.

What was the impact on other disciplines?

Nothing to report.

What was the impact on technology transfer?

Nothing to report.

What was the impact on society beyond science and technology?

Nothing to report.

CHANGES/PROBLEMS

Changes in approach and reason for change.

We deployed a back-end MongoDB database and was able to demonstrate depositing data into it. However, connecting the visualization tool directly to this data source proved to not be realistic given the time constraints and need for experimenter control. Instead we created static files that were read directly for the purpose of the experiment. This did not impact achieving the primary goals of the project and we instead demonstrated the capacity for the visualization tools to connect to a real-time data stream instead.

Actual or anticipated problems or delays and actions or plans to resolve them.

Nothing to report.

Changes that had a significant impact on expenditures.

Nothing to report.

Significant changes in the use or care of human subjects, vertebrate animals, biohazards, and/or select agents.

Nothing to report.

PRODUCTS

Publications, conference papers, and presentations

Journal publications

1. Schmidt, J. M., Miller, S., Perotte, A., Kummer, B., Doerner, J., Meyers, E., Mayer, S. A. Patient Data Visualization not Sufficient to Improve Situational Awareness. (in preparation).

Book or other non-periodical, one-time publications

1. 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.

Other publications, conference papers, and presentations

1. 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.
2. Schmidt, J. M. (2013, November). *Streaming Analytics Case Study in Columbia University Neuro-ICU* Paper presented at the EME Streaming Analytics Symposium, Chicago, Illinois.
3. Schmidt, J. M. (2014, August)*. What am I thinking about?* International Conference on Complexity of Acute Illness. Charlottesville, Virginia*.*
4. Schmidt, J. M. (2015, September). *Results from Data Visualization Cognitive Experiment.* Paper presented at the EME Streaming Analytics Symposium, Chicago, Illinois.

Website(s) or other Internet site(s)

Nothing to report

Technology or techniques

Nothing to report

Inventions, patient applications, and/or licenses

Nothing to report

Other products

1. Created a sepsis identification visualization tool to help clinicians identify patients headed for septic shock.
2. Generated a visualization tool to help clinicians assess intracranial pressure and generate patient specific physiologic set-points for goal directed therapy.
3. Created a visualization that can accept a real-time data feed.

PARTICIPANTS & OTHER COLLABORATING ORGANIZATIONS

What Individuals have worked on the project?

*Provide the following information for: (1) PDs/PIs; and (2) each person who has worked at least one person month per year on the project during the reporting period, regardless of the source of compensation (a person month equals **approximately 160 hours** of effort).*

Name:	*J. Michael Schmidt, PhD*
Project Role:	*Principal Investigator (Columbia University)*
Researcher Identifier (e.g. ORCID ID):	
Nearest person month worked:	(1.2 months per calendar year of funding; 3 years of funding: 3.6 calendar months)
Contribution to Project:	*Dr. Schmidt directed all project activities conducted at Columbia University including preparing deidentified patient data for the visualization, development of the real-time visualization tool, the preparation of patient cases for the cognitive experiment, and the execution and analysis of the cognitive experiment.*
Funding Support:	*NA*

Name:	*Sarah Miller, PhD*
Project Role:	*Subcontract site PI (Draper Laboratories)*
Researcher Identifier (e.g. ORCID ID):	
Nearest person month worked:	*(1.10 calendar months per year of funding; 3 years of funding: 3.30)*
Contribution to Project:	*Dr. Miller directed all project activities conducted by Draper Laboratory including conduction of the cognitive work analysis, development of the static visualization tool, and contributed to the design of the cognitive experiment*
Funding Support:	*NA*

Name:	*Tom Lanning, MA*
Project Role:	*Programmer (Draper Laboratories)*
Researcher Identifier (e.g. ORCID ID):	
Nearest person month worked:	*6 calendar months per year of funding; 3 years of funding: 18 calendar months**This is in replacement of the grad student that had been allocated for 12 months per calendar year***
Contribution to Project:	*Mr. Lanning was contracted by Draper Laboratory to create the static visualization tools based on the results of the cognitive work analysis and clinician feedback.*
Funding Support:	*NA*

Name:	*David Albers, PhD*
Project Role:	*Research Scientist (Columbia University)*
Researcher Identifier (e.g. ORCID ID):	
Nearest person month worked:	*0.6 calendar months per funding year; 3 years of funding: 1.8 calendar months **This is in replacement of the grad student that had been allocated for 12 months per calendar year***
Contribution to Project:	*Dr. Albers provided general computational expertise regarding empirical orthogonal functions and multivariate time series analyses.*
Funding Support:	

Name:	*Adler Perotte, MD, MA*
Project Role:	*Research Scientist (Columbia University)*
Researcher Identifier (e.g. ORCID ID):	
Nearest person month worked:	*6 calendar months per funding year; 3 years of funding: 18 calendar months **This is in replacement of the grad student that had been allocated for 12 months per calendar year***
Contribution to Project:	*Dr. Perotte developed methods to generate linear projections of physiologic data for the overview presentation, and generated data files to for use in the static visualization tool. He also provided clinical expertise to the project.*
Funding Support:	

Name:	*Stephan Mayer, MD*
Project Role:	*Professor (Columbia University)*
Researcher Identifier (e.g. ORCID ID):	
Nearest person month worked:	*0.24 calendar months per year of funding; 3 years of funding: 0.72 calendar months*
Contribution to Project:	*Dr. Mayer provided clinical expertise to the project.*
Funding Support:	*NA*

Has there been a change in the active other support of the PD/PI(s) or senior/key personnel since the last reporting period? What Individuals have worked on the project?

Dr. Miller left Draper Laboratories August 2015.

What other organizations were involved as partners?

Nothing to report.

APPENDICES

1. *Initial patient vignette*

Patient Case

Patient Vignette

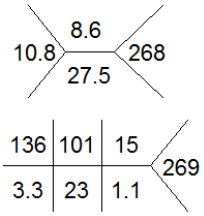
History of Present Illness:
64 year old woman with HTN and DM2 who was admitted to the CPMC NICU with Hunt & Hess Grade 3, Fisher Grade 4, modified Fisher grade 4 subarachnoid hemorrhage with early hydrocephalus. CT angiography showed no aneurysms nor evidence of radiographic vasospasm, and no aneurysm 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



41. Please copy the following text into firefox to view the patient data. To confirm that you have the correct data for this patient, please enter the last observed heart rate measurement for this period. The other questions will appear once the correct value is entered. If you have any problem please ask for help.

file:///O:/NICU/Shared%20Projects/Michael%20Schmidt/Experiment/PREDICT%20-%20v10/PREDICT/index.html#/patients/90331 *

Next

2. *Patient data presented in visualization*

3. *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														

4. *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? *

5. *Likelihood of clinical events in the 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

6. *Presented EOF composite score overview visualization*