Clinical Decision Support for Integrated Cyber-Physical Systems: A Mixed Methods Approach





Challenges

• Modern critical care units continuously monitor patient vital signs and labs, but this data is underutilized:

Studies have shown



Approximately



of alerts for drug interactions in automated drug CDS are overridden.²

- Threshold alarms are overly simplistic, mostly limited to analyzing a single data stream.
- Tools for sophisticated on-line analysis are rare.
- Most systems do not provide patient information along with alarms or individual data streams to help clinicians contextualize data.
- Access to recorded data is often difficult or impossible.
- The volume of data available can be overwhelming.

• We have attempted to overcome these challenges for a particular use-case by developing a tool to aid clinicians in detecting vasospasm, a dangerous narrowing of vessels in the brain, in post-surgical subarachnoid hemorrhage patients. We aimed to allow clinicians to accurately assess patients for vasospasm without invasive angiogram.

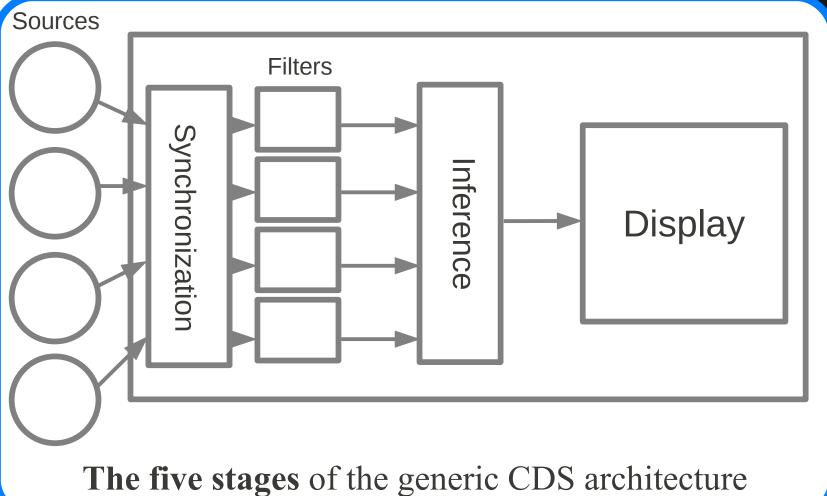
Integrated Decision Support

Clinical decision support systems provide the opportunity to overcome clinical data use challenges by:

- Utilizing a multitude of patient features from disparate sources in concert to produce a more complete picture of patient state
- Allowing the clinician to perform statistical analysis on-line.
- Presenting patient summaries and other data to clinicians in an effective way

Effective use of clinical decision support systems holds the promise of improved care, reduced mortality, and decreased healthcare costs.

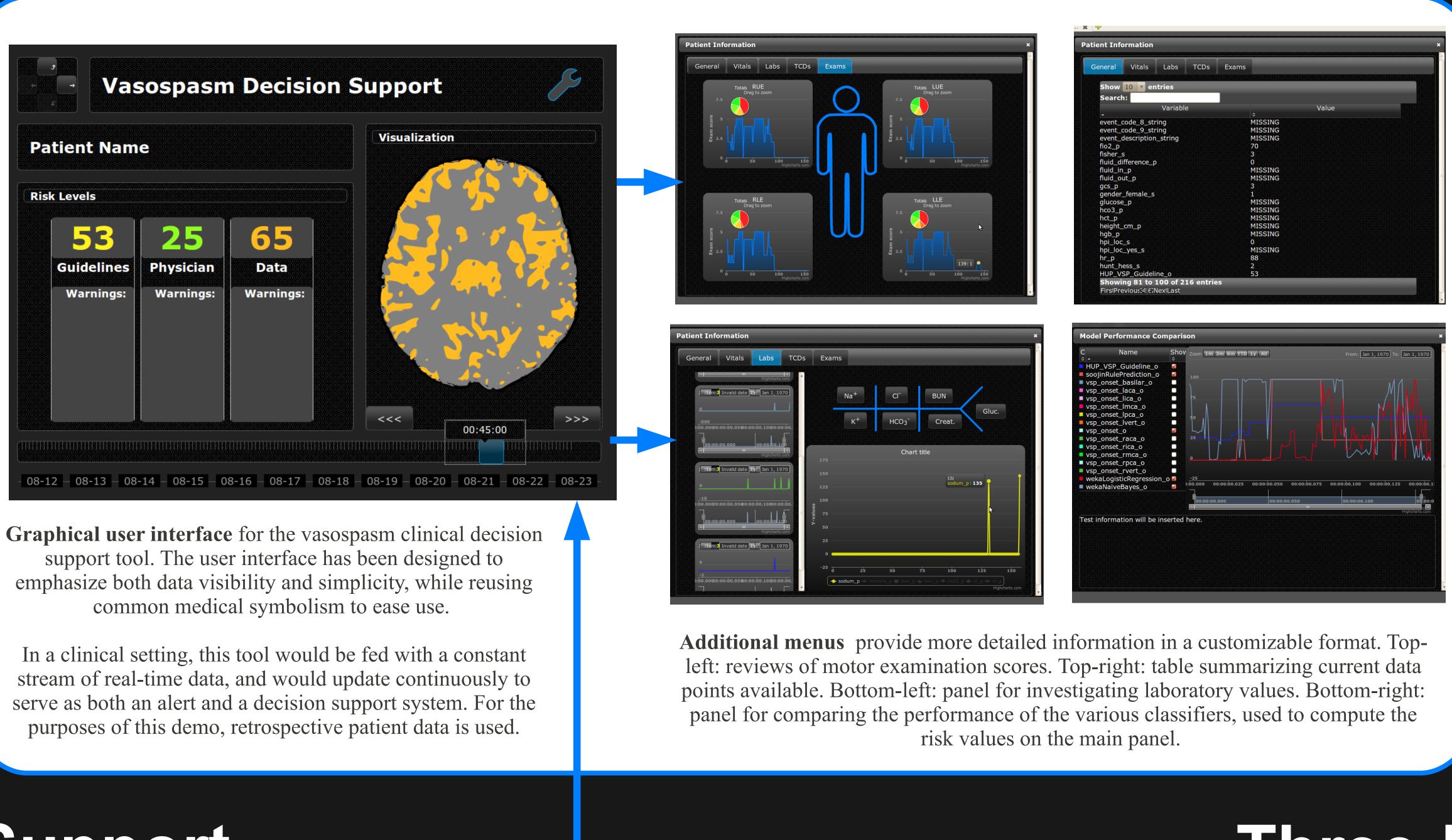
- Clinical decision support systems have failed to see widespread use.. To change this, we utilize:
- A flexible, hospital independent framework to guide design and encourage component reuse (G-CDSA).
- An analysis stage utilizing clinical guidelines, physician expertise, and data-driven models to provide increased transparency and trust.

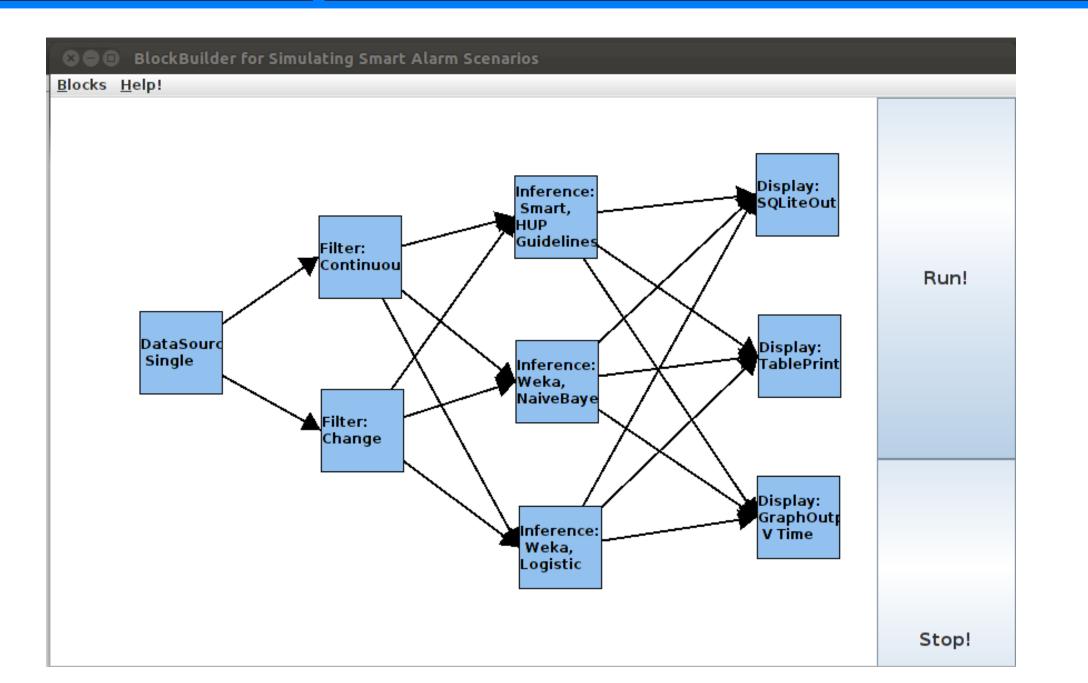


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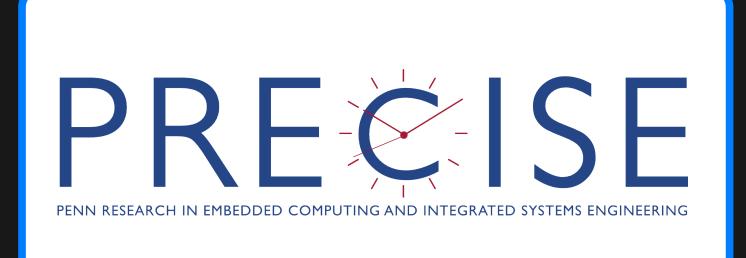
Graphical user interface for the instantiation for the G-CDSA. This interface allows reusable components to be arranged and connected into a clinical decision support system, following the principals of the G-CDSA.

1: Clark, et al. Clinical alarms in primary care. 2003, Arch Intern Med | 3. Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, Ian H. Witten (2009); The WEKA Data Intern Med | 3. Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, Ian H. Witten (2009); The WEKA Data Intern Med | 3. Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, Ian H. Witten (2009); The WEKA Data Intern Med | 3. Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, Ian H. Witten (2009); The WEKA Data Intern Med | 3. Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, Ian H. Witten (2009); The WEKA Data Intern Med | 3. Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, Ian H. Witten (2009); The WEKA Data Intern Med | 3. Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, Ian H. Witten (2009); The WEKA Data Intern Med | 3. Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, Ian H. Witten (2009); The WEKA Data Intern Med | 3. Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, Ian H. Witten (2009); The WEKA Data Intern Med | 3. Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, Ian H. Witten (2009); The WEKA Data Intern Med | 3. Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, Ian H. Witten (2009); The WEKA Data Intern Med | 3. Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, Ian H. Witten (2009); The WEKA Data Intern Med | 3. Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, Ian H. Witten (2009); The WEKA Data Intern Med | 3. Mark Hall, Eibe Frank, Geoffrey Holmes, Bernhard Pfahringer, Peter Reutemann, Ian H. Witten (2009); The WEKA Data Internation (2009); The WEKA Mining Software: An Update; SIGKDD Explorations, Volume 11, Issue 1.

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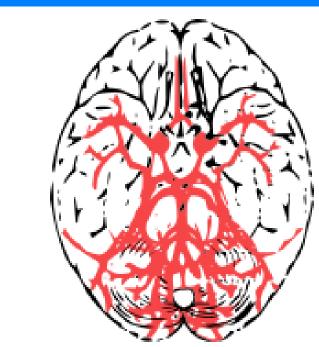
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- In the design of the analysis component of a decision support system, transparency and simplicity are key considerations, to earn clinician trust. To achieve this, we incorporate a three pronged approach:
- Prong 1: Analysis of existing clinical care guidelines • Provide hospital-wide standard of
- care • Based on wide body of literature
- Provides a "lower-bound" on system behavior
- Relatively simple, easy for humans to understand



Development

- After aneurysmal subarachnoid hemorrhage, patients are kept in the ICU for up to fourteen days to monitor for vasospasm, which can lead to ischemia if untreated. While there are clinical factors which increase suspicion for vasospasm, the ability to define its onset is made difficult by poor sensitivity of available tests.
- The only definitive measure of vasospasm is cerebral angiogram, which is invasive and resourceintensive.
- Steps for development included:
- Identification of patient features which were likely to be of use in risk assessment
- Gathering these features from retrospective patient data stores (89 patients from between 2001 and 2011 were incorporated)



Major blood vessels in the brain, where vasospasm is most easily identified through angiogram

- Surveys of clinical guidelines of the Hospital of the University of Pennsylvania, and physician interviews
- Statistical testing using Weka³

• Development of an intuitive user interface



- Prong 2: Survey of approach taken by physicians
- Leverages extensive education, refined through experience
- Could aggregate the opinions of many peers
- Offers expert opinion when none is available
- Statistical models trained on data from large patient populations.
- Leverage large amounts of retrospective patient data as "experience"
- Complexity allows them to capture nuance, subtle patterns
- Potential to identify medically novel approaches to patient risk assessment

