

Multimodality Monitoring: Informatics, Integration Data Display and Analysis

J. Michael Schmidt · Michael De Georgia ·

The Participants in the International Multidisciplinary Consensus Conference on Multimodality Monitoring

© Springer Science+Business Media New York 2014

Abstract The goal of multimodality neuromonitoring is to provide continuous, real-time assessment of brain physiology to prevent, detect, and attenuate secondary brain injury. Clinical informatics deals with biomedical data, information, and knowledge including their acquisition, storage, retrieval, and optimal use for clinical decision-making. An electronic literature search was conducted for English language articles describing the use of informatics in the intensive care unit setting from January 1990 to August 2013. A total of 64 studies were included in this review. Clinical informatics infrastructure should be adopted that enables a wide range of linear and nonlinear analytical methods be applied to patient data. Specific time epochs of clinical interest should be reviewable. Analysis strategies of monitor alarms may help address alarm fatigue. Ergonomic data display that present results from analyses with clinical information in a sensible uncomplicated manner improve clinical decision-making. Collecting and archiving the highest resolution physiologic and phenotypic data in a comprehensive open format data warehouse is a crucial first step toward information management and two-way translational research for multimodality

monitoring. The infrastructure required is largely the same as that needed for telemedicine intensive care applications, which under the right circumstances improves care quality while reducing cost.

Keywords Critical care · Data display · Data integration · Decision support · Informatics · Neuromonitoring

Introduction

The goal of multimodality neuromonitoring is to provide continuous, real-time assessment of brain physiology to help prevent, detect, and attenuate secondary brain injury. Clinical informatics deals with biomedical data, information, and knowledge including their acquisition, storage, retrieval, and optimal use for clinical decision-making. Multimodality neuromonitoring and clinical informatics have evolved in parallel and are reshaping not only how we view physiological data, but also potentially our entire approach toward scientific discovery. We are on the verge of the data-intensive science era in which hypotheses will be generated automatically among the enormous amount of data available using computational science with inductive reasoning [1]. In this new era, an integrated clinical informatics infrastructure will be essential not only to facilitate adherence to current clinical and intensive care recommendations, but also to provide the framework for two-way translational research to develop future recommendations.

Methods

This systematic review was performed according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [2].

The Participants in the International Multidisciplinary Consensus Conference on Multimodality Monitoring are listed in “Appendix”.

J. M. Schmidt (✉)
Division of Critical Care Neurology, Neurological Institute,
Columbia University College of Physicians and Surgeons, 177
Fort Washington Avenue, MHB Suite 8-300, New York,
NY 10032, USA
e-mail: mjs2134@columbia.edu

M. De Georgia
Neurocritical Care Center, Cerebrovascular Center, University
Hospital Case Medical Center and Department of Neurology,
Case Western Reserve University School of Medicine,
Cleveland, OH, USA

Search Criteria

Studies were considered to be eligible based on the PICO approach. Using the PubMed database, we conducted a systematic review from January 1990 up to the 15th of August 2013. The search strategy included the following terms: medical informatics applications, medical informatics, and medical informatics computing. This produced 29,313 articles. We combined these terms with intensive care unit (ICU) to narrow the search down to 976 articles. We restricted articles to those published in the English. Unpublished data or congress presentations/abstracts were not considered.

Study Selection and Data Collection

One author independently reviewed all citations, abstracts, and full-text articles to select eligible studies. Excluded were: (a) case reports or case-series with ≤ 5 patients; (b) experimental animal studies. Data were abstracted using a predefined abstraction spreadsheet, according to the PICO system. No attempt was made to re-analyze the data, and no meta-analysis was performed since there are insufficient randomized (RCT) or case-control studies. Furthermore, since clinical informatics is a dynamic and rapidly evolving field and at present rigorous evidence on how clinical informatics impacts multimodality monitoring as a field is still being elucidated we included review articles and studies conducted in any critical care population as candidate studies. Sixty-four studies were included in the final review. The second author checked data extraction accuracy.

Review End-Points

1. What clinical informatics infrastructure is required to collect bedside physiologic monitoring data?
2. Is it essential to analyze multimodality data to extract clinically relevant information?
3. What are effective ways to present multimodal monitoring data to clinicians to best enable fast and accurate treatment decisions?
4. Is there benefit to investing in telemedicine intensive care technologies?

Literature Summary

The informatics infrastructure necessary for clinical multimodality neuromonitoring and two-way translational research includes three interdependent elements that

together compose a clinical translational research platform: (1) Acquisition, synchronization, integration, and storage of all relevant patient data into a single, searchable database, data repository, or enterprise-level clinical data warehouse; (2) Data processing and analysis to extract clinically relevant features from raw data and translate them into actionable clinical information; (3) Data visualization of actionable information at the bedside in a manner that provides clinicians with situational awareness of patient state or changes in patient state [3], along with integration of clinical information into clinical practice and workflow.

Data Acquisition

Collecting and archiving data is the crucial first step toward information management. A typical patient in a Neurocritical Care Unit (NCCU) may undergo frequent or continuous monitoring of many physiological parameters (e.g., blood pressure, heart rate) along with neuromonitoring of intracranial pressure (ICP), continuous EEG, brain tissue oxygen tension, cerebral blood flow, and microdialysis parameters. An enormous amount of data is generated reflecting dynamic and complex physiology. Dynamic systems are based on relationships that can only be understood by data integration. Most parameters are generated from stand-alone medical devices that do not easily integrate with one another. For years, data acquisition and integration have been confounded by incompatibilities among monitoring equipment, proprietary limitations from industry, and the absence of standard data formatting. More than 90 % of hospitals recently surveyed by the Healthcare Information and Management Systems Society (HIMSS) use six or more types of medical devices and only about a third integrate them with one another or with their EHRs [4].

Currently, there are two basic approaches to acquire and store high-resolution data: kiosk-type portable cart-based systems that can be moved from room to room and distributed systems in which data from bedside monitors are sent continuously to a remote server. The kiosk-type systems provide a limited set of patient-specific clinical analyses that can be performed one patient at a time and presented to clinicians in real-time at the bedside. They tend to be easy to use by clinical staff and easy to maintain. Purchasing a portable cart-based system is akin to purchasing a medical device. However, data may not be stored in an open database format limiting its use to the way it is analyzed and presented on the device screen.

The second approach is to simultaneously collect all data from the bedside monitor and the devices, and store it on an enterprise-level central server [5, 6] with large computational and storage capacities necessary to manage,

store, and retrieve patient data [7]. Operation of a central server will require a support budget and information technology staff to maintain it. A key benefit is that data are more accessible, although analysis and bedside presentation of information are still required. Barriers related to data security and systems architecture have also made implementation of distributed systems challenging. EEG data need to be acquired separately and there are currently no standard practices to accomplish this. Kull and Emerson [8] review general considerations related to EEG monitoring in the intensive care unit.

There are no specific guidelines regarding the optimal sampling frequency, and the most prudent course is to acquire data at the highest possible sampling frequency. Data are essentially meaningless unless annotated so that providers can search for “epochs of interest.” The value of annotated high-resolution physiological data cannot be overstated [9]. Common terminologies, data models, and annotation standards are needed so that the same tools can be used across healthcare. Once a comprehensive database of integrated, precisely time-stamped physiologic signals is created and complemented by relevant clinical observations, laboratory results, and imaging data, clinicians can then begin to formulate and test hypotheses about the underlying dynamic physiological systems in patients.

Data Processing and Analysis

Neurocritical care has evolved to become a very data-intensive field. The promise of clinical informatics lies in the potential to use a wide array of advanced and novel analytical techniques on high-resolution, multidimensional, multimodal physiological data in order to develop a better understanding of the complex relationships among various physiological parameters, enhance the ability to predict future events, and improve outcome.

Simple indices may be calculated using informatics that adds information to patient assessment. For instance, calculating the area under the curve (AUC) above a specific cut point of temperature (such as $>38.5^{\circ}\text{C}$) provides a more robust measure of “dose” of fever that can be used to track the effectiveness of interventions such as fever control or hypothermia therapy [10]. The moving correlation coefficient between MAP and ICP is used to generate the pressure reactivity index which provides information about whether cerebral pressure autoregulation is intact. The PRx has been used to determine the optimal CPP for patient management after traumatic brain injury (TBI) and intracerebral hemorrhage [11, 12].

Techniques for the analysis of nonlinear systems (complex systems analysis) have emerged from the mathematical

and engineering sciences [13]. Time series analysis, for example, measures variation over time. This has been most often applied to the heart rate by evaluating intervals between consecutive QRS complexes. Decreased variability is thought to reflect system isolation and a reduced ability to respond to perturbations. Decreased heart rate variability is associated with poor outcome in patients with myocardial infarction [14] and heart failure [15]. Similarly, reduced ICP variability may be a better predictor of outcome than the measure usually displayed at the bedside, mean ICP [16]. Frequency domain (spectral) analysis displays the contributions of each sine wave as a function of its frequency (using Fourier transformation). Changes in spectral heart rate variability have been demonstrated in hypovolemia [17], hypertension [18], coronary artery disease [19], renal failure [20], depth of anesthesia [21], and more. Approximate entropy (ApEn) provides a measure of the degree of randomness within a series of data. Heart rate ApEn decreases with age [22] and is predictive of atrial fibrillation [23]. Hornero and colleagues showed that ICP ApEn decreases as elevated ICP develops [24]. Papaioannou et al. [25] also demonstrated that, among critically ill patients, nonsurvivors had lower ApEn compared to survivors. Detrended fluctuation analysis is a technique for describing “fractal” scaling behavior of variability in physiological signals (similar patterns of variation across multiple time scales). Altered “fractal scaling” of the ICP signal is associated with poor outcome [26]. The study of normal and pathologic dynamics using an array of these complex systems analysis methods may give us fresh insights into normal physiologic relationships and the pathobiology of critical illness leading to new mathematical models that are more accurate and realistic [27].

Conceptualizing patients as existing in physiologic and pathophysiologic “states” has led to the idea that therapies may need to be redirected toward facilitating transitions toward favorable physiologic states as opposed to “fixing” particular physiologic variables [3, 28]. These states and the transitions among them are invisible to clinicians using spreadsheet-based ICU patient records, but may be assessed using model-based analytic methods borrowed from other scientific disciplines. Dynamical system models describe how systems evolve over time based on classical mechanics such as pressure–volume–flow relationships. The nonlinear nature of these systems requires a more holistic approach to data analysis that incorporates all the interconnections and coupling between organ systems and may be conceptually better suited to the complex environment of neurocritical care [29–31]. Given the complexity of all this critical care data, a systematic real-time classification process for understanding a patient’s condition is needed.

Data Visualization and Workflow

Clinicians may be confronted with more than 200 variables [32, 33] during rounds of critically ill patients each morning yet most people cannot judge the degree of relatedness between more than two variables [34]. While experienced clinicians are very good at sifting through and disregarding information to find meaning in data, [35] our ability to acquire data has outstripped our ability to understand it [36] and this greatly contributes to “information overload” that can lead to preventable medical errors [34, 37]. In the Neurocritical Care Unit, patient records are typically presented as text. Woods [38] found, however, that a text display alone increases the probability of error because users must collect, maintain, and integrate all the data mentally. The goal of data visualization is to provide clinical decision support that enhances clinician situational awareness about the patient state. The way information is represented significantly affects problem solving [39–44], and impacts the conclusions likely to be drawn from the display [45]. Data visualization development should, therefore, follow an iterative, human-centered design methodology to effectively arrange information to support the cognitive process of clinicians [41, 43] while avoiding adversely affecting clinical decision-making [46]. Such an approach also limits the prospect of project failure due to non-technology and human factors [47], or insufficient training [48].

Graphical displays and patient summaries enhanced or outperformed traditional text displays in numerous studies. Koch et al. [49] showed that nurses were able to answer questions about the patient’s status and treatment significantly faster and more accurately simply by providing an integrated display that contained all the information on a single screen. Pulling out the critical information from the health record and presenting it as a summary reduced the time required for making decisions and improved the quality of decisions [50, 51]. Displaying a representation of a patient’s history in a timeline led to up to a 50 % reduction in response time in finding connections among events [52], and recall has been found to improve with graphical displays [53]. User satisfaction can be enhanced using an ecological display even without performance benefits [54].

There are several challenges to representing multivariate patient data in a single visual display. Physiological data have a dense structure due to its volume and high dimensionality making it challenging for users to explore relationships intuitively and interactively while still maintaining the intrinsic physiologic meaning of specific measurements [55]. Graphic attributes that make up ICU visualizations must be chosen carefully to avoid inducing cognitive overload—the problem it is meant to solve—by

combining too many elements into a single display [56], which has been found to actually worsen clinician detection of critical events [54]. Indeed, under conditions requiring processing of multiple data streams computational algorithms have been shown to outperform clinicians using an ecological display [57, 58] supporting the tremendous need for automated decision support systems in medicine [48].

Telemedicine Intensive Care

The Committee on Manpower for Pulmonary and Critical Care Societies released a workforce study detailing a projected shortfall of critical care healthcare providers over the next 30 years [59]. Many hospitals also lack the patient volume or financial resources to hire dedicated intensivists and staff. It has been suggested that a telemedicine intensive care (tele-ICU) model could help close this gap [60] when a well-supported intensivist may staff approximately 50–100 remote beds [61]. Telemedicine intensive care leverages videoconferencing technology, telemetry, and the electronic medical record to provide and support health care when distance separates the patient and the caregiver [62, 63]. A recent telemedicine consensus statement recommended that the use of on-site full-time or part-time intensivists is the most efficient first step toward improving critical care quality [61].

The aims of “Patient-Focused Critical Care Enhancement Act” (H.R. 1581) is to “optimize the delivery of critical care medicine and expand the critical care workforce” by focusing on “standardization of critical care protocols, intensive care unit layout, equipment interoperability, and medical informatics,” mainly with the goal of improving telemedicine services [64]. At its core, telemedicine is about the re-engineering of the systems we use to deliver care. Whether these systems are used to monitor a patient located 3,000 miles away or 3 feet away, the underlying principles—equipment interoperability, data acquisition, synchronization, medical informatics—are equally applicable. Investment in this basic information technology architecture is absolutely necessary. This is what will drive the next generation of Tele-ICU care.

Conclusion

Multimodality neuromonitoring is now routinely used in neurocritical care for detection and management of secondary brain injury. The success of advanced informatics in other areas of medicine such as epidemiology, genetics, and pharmacology has led to interest in the development of clinical informatics as a way to provide new insight into the

complex physiological relationships in patients with acute brain injury. We are now entering the data-intensive science era. Through advances in technology and a coordinated effort involving clinicians, engineers, computer scientists, and experts in informatics we are beginning to make the goal of an integrated clinical informatics infrastructure to support multimodality monitoring achievable by combining modern signal processing, computational modeling, complex systems analysis, knowledge-based clinical reasoning, and clear, clinician-centric visualization tools. We believe that such an integrated clinical informatics infrastructure will play an increasingly important in neurocritical care and will provide the framework for two-way translational research to develop future recommendations.

Recommendations (and see Summary Statement)

1. We recommend utilizing ergonomic data displays that present clinical information in a sensible uncomplicated manner to reduce cognitive load and improve judgments of clinicians (Strong recommendation, Moderate quality of evidence).
2. We suggest using clinical decision support tools such as algorithms that automatically process multiple data streams with the results presented on a simple, uncomplicated display (Weak recommendation, Moderate quality of evidence).
3. We recommend adopting a database infrastructure that enables the integration of high-resolution physiologic data (including EEG recordings) with lower resolution data from laboratory and electronic health care systems (Strong recommendation, Low quality of evidence).
4. We recommend following an iterative, human-centered design methodology for complex visualization displays to avoid adversely affecting clinical decision-making (Strong recommendation, Moderate quality of evidence).
5. We recommend device manufacturers utilize data communication standards including time synchronization on all devices to improve usability of its data (Strong recommendation, Low quality of evidence).
6. We recommend adopting “smart” alarms in the intensive care unit to help address alarm fatigue (Strong recommendation, Low quality of evidence).

Additional Conclusions

Should data from specific time epochs of clinical interest be reviewable to improve clinician understanding of patient status?

- Data from specific time epochs of clinical interest should be reviewable by the clinician. The clinician is

advised to work with data collection vendors to enable this feature (Low quality of evidence).

Should classical statistical methods (e.g., mean, variance, correlation) and/or advanced analytic methods (e.g., signal processing, complex systems analysis) methods be applied to physiological data to improve clinician understanding of patient status?

- A wide range of linear and nonlinear analytical methods should be applied to examine physiological data (Moderate quality of evidence).

What type of data should be collected?

- Collecting and archiving physiologic data (waveform signals and numeric data) and phenotypic data (lab results, imaging, nursing notes) in a comprehensive data warehouse is the crucial first step toward information management (Low quality of evidence).

In what format should data be stored?

- All high-resolution physiological data should be stored in a non-relational open database format (Low quality of evidence).

Is a distributed data whole ICU collection system or kiosk-type cart that moves room to room better for data acquisition?

- There are advantages and disadvantages to each approach and what is used will depend on the specifications and needs of the intensive care unit. (Low quality of evidence).

Should data monitoring be centralized using telemedicine technology such that one or two dedicated clinicians monitor multiple patients to detect problems?

- The infrastructure required for telemedicine is similar to what is needed in general and so ICUs should invest in an informatics infrastructure that supports care delivery whether the clinician are 3000 miles away or 3 feet away from the patient. (Low quality of evidence).

What parameters should devices transmit?

- Device manufacturers should enable devices to transmit all parameters that the device generates including non-proprietary device status parameters to improve clinical usability of its data (Low quality of evidence).

At what frequency should devices transmit data?

- Device manufacturers should provide data at the highest frequency generated by the device (Low quality of evidence).

Should devices output summary measurements (e.g., average values) of its measurements?

- Device manufacturers should provide raw measurements first and foremost, but also provide summary measurements as needed (Low quality of evidence).

Acknowledgments J. Michael Schmidt has received Grants by the Department of Defense, the Dana Foundation, C.S. Draper Laboratory, and IBM Research.

Conflict of interest Michael De Georgia declares that he has no conflicts of interest.

Appendix 1: Participants in the International Multi-disciplinary Consensus Conference on Multimodality Monitoring

Peter Le Roux, MD, FACS
Brain and Spine Center
Suite 370, Medical Science Building
Lankenau Medical Center
100 East Lancaster Avenue, Wynnewood, PA 19096, USA
Tel: +1 610 642 3005;
Fax: 610 642 3057
lerouxp@mlhs.org

David K Menon MD PhD FRCP FRCA FFICM FMedSci
Head, Division of Anaesthesia, University of Cambridge
Consultant, Neurosciences Critical Care Unit
Box 93, Addenbrooke's Hospital
Cambridge CB2 2QQ, UK
dkm13@wbic.cam.ac.uk

Paul Vespa, MD, FCCM, FAAN, FNCS
Professor of Neurology and Neurosurgery
Director of Neurocritical Care
David Geffen School of Medicine at UCLA
Los Angeles, CA 90095 USA
PVespa@mednet.ucla.edu

Giuseppe Citerio, MD
Director NeuroIntensive Care Unit
Department of Anesthesia and Critical Care
Ospedale San Gerardo, Monza.
Via Pergolesi 33, Monza 20900, Italy
g.citerio@hsgerardo.org

Mary Kay Bader RN, MSN, CCNS, FAHA, FNCS
Neuro/Critical Care CNS
Mission Hospital
Mission Viejo CA 92691, USA
Marykay.Bader@stjoe.org

Gretchen M. Brophy, PharmD, BCPS, FCCP, FCCM
Professor of Pharmacotherapy & Outcomes Science and
Neurosurgery
Virginia Commonwealth University
Medical College of Virginia Campus
410 N. 12th Street
Richmond, Virginia 23298-0533 USA
gbrophy@vcu.edu

Michael N. Diringer, MD
Professor of Neurology, Neurosurgery & Anesthesiology
Chief, Neurocritical Care Section
Washington University
Dept. of Neurology, Campus Box 8111
660 S Euclid Ave
St Louis, MO 63110 USA
diringer@neuro.wustl.edu

Nino Stocchetti, MD
Professor of Anesthesia and Intensive Care
Department of physiopathology and transplant
Milan University
Director Neuro ICU
Fondazione IRCCS Cà Granda Ospedale Maggiore Policlinico
Via F Sforza, 35 20122 Milan Italy
e-mail stocchet@policlinico.mi.it

Walter Videtta, MD
ICU Neurocritical Care
Hospital Nacional 'Prof. a. Posadas'
El Palomar - Pcia. de Buenos Aires
Argentina
wvidetta@ar.inter.net

Rocco Armonda, MD
Department of Neurosurgery
MedStar Georgetown University Hospital
Medstar Health, 3800 Reservoir Road NW
Washington DC 20007
USA
Rocco.Armonda@gmail.com

Neeraj Badjatia, MD
Department of Neurology
University of Maryland Medical Center
22 S Greene St
Baltimore, MD, 21201
USA
nbadjatia@umm.edu

Julian Boesel, MD
Department of Neurology
Ruprecht-Karls University

Hospital Heidelberg, Im Neuenheimer Feld 400
D-69120 Heidelberg
Germany
Julian.Boesel@med.uni-heidelberg.de

Randal Chesnut, MD, FCCM, FACS
Harborview Medical Center,
University of Washington Mailstop 359766
325 Ninth Ave
Seattle WA 98104-2499
USA
chesnutr@u.washington.edu

Sherry Chou, MD, MMSc
Department of Neurology
Brigham and Women's Hospital
75 Francis Street
Boston MA 02115
USA
schoul@partners.org

Jan Claassen, MD, PhD, FNCS
Assistant Professor of Neurology and Neurosurgery
Head of Neurocritical Care and Medical Director of the
Neurological Intensive Care Unit
Columbia University College of Physicians & Surgeons
177 Fort Washington Avenue, Milstein 8 Center room 300
New York, NY 10032
USA
jc1439@cumc.columbia.edu

Marek Czosnyka, PhD
Department of Neurosurgery
University of Cambridge
Addenbrooke's Hospital, Box 167
Cambridge, CB20QQ
United Kingdom
mc141@medschl.cam.ac.uk

Michael De Georgia, MD
Professor of Neurology
Director, Neurocritical Care Center
Co-Director, Cerebrovascular Center
University Hospital Case Medical Center
Case Western Reserve University School of Medicine
11100 Euclid Avenue
Cleveland, Ohio 44106
michael.degeorgia@uhhospitals.org

Anthony Figaji, MD, PhD
Head of Pediatric Neurosurgery
University of Cape Town
617 Institute for Child Health

Red Cross Children's Hospital
Rondebosch, 7700 Cape Town
South Africa
anthony.figaji@uct.ac.za

Jennifer Fugate, DO
Department of Neurology
Mayo Clinic
200 First Street SW
Rochester, MN 55905
Fugate.Jennifer@mayo.edu

Raimund Helbok, MD
Department of Neurology, Neurocritical Care Unit
Innsbruck Medical University
Anichstr.35, 6020
Innsbruck,
Austria
raimund.helbok@uki.at

David Horowitz, MD
Associate Chief Medical Officer
University of Pennsylvania Health System
3701 Market Street
Philadelphia, PA, 19104
USA
david.horowitz@uphs.upenn.edu

Peter Hutchinson, MD
Professor of Neurosurgery
NIHR Research Professor
Department of Clinical Neurosciences
University of Cambridge
Box 167 Addenbrooke's Hospital
Cambridge CB2 2QQ
United Kingdom
pjah2@cam.ac.uk

Monisha Kumar, MD
Department of Neurology
Perelman School of Medicine, University of
Pennsylvania
3 West Gates
3400 Spruce Street
Philadelphia, PA, 19104
USA
monisha.kumar@uphs.upenn.edu

Molly McNett, RN, PhD
Director, Nursing Research
The MetroHealth System
2500 MetroHealth Drive
Cleveland, OH 44109

USA
mmcnett@metrohealth.org

Chad Miller, MD
Division of Cerebrovascular Diseases and Neurocritical Care
The Ohio State University
395 W. 12th Ave, 7th Floor
Columbus, OH 43210
ChadM.Miller@osumc.edu

Andrew Naidech, MD, MSPH
Department of Neurology
Northwestern University Feinberg SOM 710
N Lake Shore Drive, 11th floor
Chicago, IL 60611
ANaidech@nmff.org

Mauro Oddo, MD
Department of Intensive Care Medicine
CHUV University Hospital, BH 08-623
Faculty of Biology and Medicine University of Lausanne
1011 Lausanne, Switzerland
Mauro.Oddo@chuv.ch

DaiWai Olson, RN, PhD
Associate Professor of Neurology, Neurotherapeutics and Neurosurgery
University of Texas Southwestern
5323 Harry Hines Blvd.
Dallas, TX 75390-8897
USA
daiwai.olson@utsouthwestern.edu

Kristine O'Phelan M.D.
Director of Neurocritical Care
Associate Professor, Department of Neurology
University of Miami, Miller School of Medicine
JMH, 1611 NW 12th Ave, Suite 405
Miami, FL, 33136
USA
kophelan@med.miami.edu

Javier Provencio, MD
Associate Professor of Medicine
Cerebrovascular Center and Neuroinflammation Research Center
Lerner College of Medicine
Cleveland Clinic
9500 Euclid Ave, NC30
Cleveland, OH 44195
USA
provenj@ccf.org

Corina Puppo, MD
Assistant Professor, Intensive Care Unit
Hospital de Clinicas, Universidad de la República
Montevideo
Uruguay
coripuppo@gmail.com

Richard Riker, MD
Critical Care Medicine
Maine Medical Center
22 Bramhall Street
Portland, Maine 04102-3175
USA
RRiker@cmamaine.com

Claudia Robertson, MD
Department of Neurosurgery
Medical Director of Center for Neurosurgical Intensive Care
Ben Taub Hospital
Baylor College of Medicine
1504 Taub Loop, Houston, TX 77030
USA
claudiar@bcm.tmc.edu

J. Michael Schmidt, PhD, MSc
Director of Neuro-ICU Monitoring and Informatics
Columbia University College of Physicians and Surgeons
Milstein Hospital 8 Garden South, Suite 300
177 Fort Washington Avenue
New York, NY 10032
USA
mjs2134@columbia.edu

Fabio Taccone, MD
Department of Intensive Care, Laboratoire de Recherche Experimentale
Erasmé Hospital
Route de Lennik, 808
1070 Brussels
Belgium
ftaccone@ulb.ac.be

References

1. Bellazzi R, Diomidous M, Sarkar IN, Takabayashi K, Ziegler A, McCray AT. Data analysis and data mining: current issues in biomedical informatics. *Methods Inf Med.* 2011;50:536–44.
2. Liberati A, Altman DG, Tetzlaff J, et al. The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: explanation and elaboration. *Ann Intern Med.* 2009;151:W-65–94.
3. Buchman TG. Novel representation of physiologic states during critical illness and recovery. *Crit Care.* 2010;14:127.

4. Medical devices landscape: current and future adoption, integration with EMRs, and connectivity. 2010. (Accessed June 6, 2013, at www.himssanalytics.org/docs/medicaldevices_landscape).
5. Chelico J, PhD A, Wajngurt D. Architectural design of a data warehouse to support operational and analytical queries across disparate clinical databases. 2007. p. 901.
6. Martich G, Waldmann C, Imhoff M. Clinical informatics in critical care. *J Intensiv Care Med*. 2004;19:154.
7. Chou D, Sengupta S. Infrastructure and security. Burlington: Academic Press; 2008.
8. Kull L, Emerson R. Continuous EEG monitoring in the intensive care unit: technical and staffing considerations. *J Clin Neurophysiol*. 2005;22:107–18.
9. Signorini DF, Piper IR, Jones PA, Howells TP. Importance of textual data in multimodality monitoring. *Crit Care Med*. 1997;25:2048–50.
10. Diring MN. Treatment of fever in the neurologic intensive care unit with a catheter-based heat exchange system. *Crit Care Med*. 2004;32:559–64.
11. Diedler J, Sykora M, Rupp A, et al. Impaired cerebral vasomotor activity in spontaneous intracerebral hemorrhage. *Stroke*. 2009;40:815–9.
12. Steiner LA, Czosnyka M, Piechnik SK, et al. Continuous monitoring of cerebrovascular pressure reactivity allows determination of optimal cerebral perfusion pressure in patients with traumatic brain injury. *Crit Care Med*. 2002;30:733–8.
13. Goldberger AL. Applications of chaos to physiology and medicine. In: Kim JH, Stringer J, editors. *Applied chaos*. New York: Wiley; 1992. p. 321–31.
14. Kleiger RE, Miller JP, Bigger JT Jr, Moss AJ. Decreased heart rate variability and its association with increased mortality after acute myocardial infarction. *Am J Cardiol*. 1987;59:256–62.
15. Szabo BM, van Veldhuisen DJ, van der Veer N, Brouwer J, De Graeff PA, Crijns HJ. Prognostic value of heart rate variability in chronic congestive heart failure secondary to idiopathic or ischemic dilated cardiomyopathy. *Am J Cardiol*. 1997;79:978–80.
16. Kirkness CJ, Burr RL, Mitchell PH. Intracranial pressure variability and long-term outcome following traumatic brain injury. *Acta Neurochir Suppl*. 2008;102:105–8.
17. Friedman JK, Cohen RJ, Saul JP. Mild hypovolemic stress alters autonomic modulation of heart rate. *Hypertension*. 1993;21:236–47.
18. Mussalo H, Vanninen E, Ikaheimo R, et al. Heart rate variability and its determinants in patients with severe or mild essential hypertension. *Clin Physiol*. 2001;21:594–604.
19. van Boven AJ, Jukema JW, Haaksma J, Zwinderman AH, Crijns HJ, Lie KI. Depressed heart rate variability is associated with events in patients with stable coronary artery disease and preserved left ventricular function. REGRESS Study Group. *Am Heart J*. 1998;135:571–6.
20. Axelrod S, Lishner M, Oz O, Bernheim J, Ravid M. Spectral analysis of fluctuations in heart rate: an objective evaluation of autonomic nervous control in chronic renal failure. *Nephron*. 1987;45:202–6.
21. Towell DL, Kovarik WD, Carr R, et al. Linear and nonlinear analysis of heart rate variability during propofol anesthesia for short-duration procedures in children. *Pediatr Crit Care Med*. 2003;4:308–14.
22. Ryan SM, Goldberger AL, Pincus SM, Mietus J, Lipsitz LA. Gender- and age-related differences in heart rate dynamics: are women more complex than men? *J Am Coll Cardiol*. 1994;24:1700–7.
23. Vikman S, Makikallio TH, Yli-Mayry S, et al. Altered complexity and correlation properties of R-R interval dynamics before the spontaneous onset of paroxysmal atrial fibrillation. *Circulation*. 1999;100:2079–84.
24. Hornero R, Aboy M, Abasolo D, McNames J, Goldstein B. Interpretation of approximate entropy: analysis of intracranial pressure approximate entropy during acute intracranial hypertension. *IEEE Trans Biomed Eng*. 2005;52:1671–80.
25. Papaioannou VE, Maglaveras N, Houvarda I, Antoniadou E, Vretzakis G. Investigation of altered heart rate variability, nonlinear properties of heart rate signals, and organ dysfunction longitudinally over time in intensive care unit patients. *J Crit Care*. 2006;21:95–103 discussion-4.
26. Burr RL, Kirkness CJ, Mitchell PH. Detrended fluctuation analysis of intracranial pressure predicts outcome following traumatic brain injury. *IEEE Trans Biomed Eng*. 2008;55:2509–18.
27. Buchman TG. Nonlinear dynamics, complex systems, and the pathobiology of critical illness. *Curr Opin Crit Care*. 2004;10:378–82.
28. Buchman TG. Physiologic stability and physiologic state. *J Trauma*. 1996;41:599–605.
29. Godin PJ, Buchman TG. Uncoupling of biological oscillators: a complementary hypothesis concerning the pathogenesis of multiple organ dysfunction syndrome. *Crit Care Med*. 1996;24:1107–16.
30. Coveney PV, Fowler PW. Modelling biological complexity: a physical scientist's perspective. *J R Soc Interface*. 2005;2:267–80.
31. Jacono FF, DeGeorgia MA, Wilson CG, Dick TE, Loparo KA. Data acquisition and complex systems analysis in critical care: developing the intensive care unit of the future. *J Healthc Eng*. 2010;1:336–7.
32. Morris G, Gardner R. Computer applications. In: Hall J, Schmidt G, Wood L, editors. *Principles of critical care*. New York: McGraw-Hill; 1992. p. 500–14.
33. Morris A, Gardner R. Computer applications. *Principles of critical care*. New York: McGraw-Hill; 1992. p. 500–14.
34. Imhoff M. Detecting relationships between physiological variables using graphical modeling. Annual Symposium, Proceedings of the AMIA; 2002.
35. Woods DD, Patterson ES, Roth EM. Can we ever escape from data overload? A cognitive systems diagnosis. *Cogn Technol Work*. 2002;4:22–36.
36. De Turck F, Decruyenaere J, Thysebaert P, et al. Design of a flexible platform for execution of medical decision support agents in the intensive care unit. *Comput Biol Med*. 2007;37:97–112.
37. Jennings D, Amabile T, Ross L. Informal assessments: data-based versus theory-based judgments. In: Kahnemann D, Slovic P, Tversky A, editors. *Judgments under uncertainty: heuristics and biases*. Cambridge: Cambridge University Press; 1982. p. 211–30.
38. Woods D. Human-Computer Interaction and Complex Systems. London: The cognitive engineering of problem representations. Academic Press; 1991. p. 169–88.
39. Zhang J, Norman DA. Representations in distributed cognitive tasks. *Cognit Sci*. 1994;18:87–122.
40. Roth EM, Patterson ES, Mumaw RJ. Cognitive engineering: issues in user-centered system design. *Encyclopedia of software engineering*. New York: Wiley; 2002. p. 163–79.
41. Tufte E, editor. *Envisioning information*. Cheshire: Graphic Press; 1990.
42. Tufte ER. *The visual display of quantitative information*. Cheshire: Graphics press; 1983.
43. Tufte ER. *Envisioning information*. 1990. Visual Explanations: Images and Quan 2006.
44. Woods DD. Visual momentum: a concept to improve the cognitive coupling of person and computer. *Int J Man Mach Stud*. 1984;21:229–44.
45. Keim DA. Designing pixel-oriented visualization techniques: theory and applications. *IEEE Trans Vis Comput Gr*. 2000;6:59–78.
46. Faiola A, Newlon C. Advancing Critical Care in the ICU: A human-centered biomedical data visualization systems. *Ergonomics and Health Aspects of Work with Computers* 2011:119–28.

47. Zhang J. Human-centered computing in health information systems Part 1: analysis and design. *J Biomed Inform.* 2005;38:1–3.
48. Ordóñez P, desJardins M, Lombardi M, Lehmann CU, Fackler J. An animated multivariate visualization for physiological and clinical data in the ICU. 2010: ACM. p. 771–9.
49. Koch S, Staggers N, Weir C, Agutter J, Liu D, Westenskow D. Integrated Information Displays for ICU Nurses: Field Observations, Display Design, and Display Evaluation. 2010: SAGE Publications. pp. 932–6.
50. Elson RB, Connelly DP. The impact of anticipatory patient data displays on physician decision making: a pilot study. 1997: American Medical Informatics Association. p. 233.
51. Balas EA. Interactive computer graphics support of medical decision-making: Department of Medical Informatics, University of Utah; 1991.
52. Plaisant C, Milash B, Rose A, Widoff S, Shneiderman B. LifeLines: visualizing personal histories. 1996: ACM. pp. 221–7.
53. Alonso D, Rose A, Plaisant C, Norman K. Viewing personal history records: a comparison of tabular format and graphical presentation using lifelines. *Behav Inf Technol.* 1997;17:249–62.
54. Effken JA, Loeb RG, Kang Y, Lin ZC. Clinical information displays to improve ICU outcomes. *Int J Med Inf.* 2008;77:765–77.
55. Chan WW-Y. A survey on multivariate data visualization. Department of Computer Science and Engineering Hong Kong University of Science and Technology 2006;8:1–29.
56. Healey CG. Perception in visualization. Department of Computer Science, North Carolina State University, available at: <http://www.csc.ncsu.edu/faculty/healey/PP/2005>. Accessed 14 June 2013.
57. Moody GB, Lehman L. Predicting acute hypotensive episodes. The 10th annual physioNet/computers in cardiology challenge. *Computers in Cardiology*, 2009: IEEE pp. 541–4.
58. M.I.T. Laboratory of Computational Physiology, Physionet challenge; 2009. <http://physionet.org/challenge/2009/>. Accessed 20 June 2013.
59. Angus D, Kelley M, Schmitz R, White A, Popovich J Jr. Caring for the critically ill patient. Current and projected workforce requirements for care of the critically ill and patients with pulmonary disease: can we meet the requirements of an aging population? *JAMA.* 2000;284:2762–70.
60. Young LB, Chan PS, Lu X, Nallamothu BK, Sasson C, Cram PM. Impact of telemedicine intensive care unit coverage on patient outcomes: a systematic review and meta-analysis. *Arch Intern Med.* 2011;171:498.
61. Cummings J, Krsek C, Vermoch K, Matuszewski K. Intensive care unit telemedicine: review and consensus recommendations. *AmMed Qual.* 2007;22:239–50.
62. Field MJ, Grigsby J. Telemedicine and remote patient monitoring. *JAMA.* 2002;288:423–5.
63. Chapman M, Gattas D, Suntharalingam G. Innovations in technology for critical care medicine. *Crit Care.* 2004;8:74–6.
64. H.R. 1581. The Patient-Focused Critical Care Enhancement Act, March 18, 2009.