MEDINFO 2017: Precision Healthcare through Informatics
A.V. Gundlapalli et al. (Eds.)

doi:10.3233/978-1-61499-830-3-308

Developing Visual Thinking in the Electronic Health Record

Andrew D. Boyd[a], Christine D. Young[a], Margret Amatayakul[b], Michael G Dieter[a], Lawrence M Pawola[a]

[a] *Department of Biomedical and Health Information Sciences, University of Illinois at Chicago, Chicago, Illinois, U.S.A,*
[b] *College of Applied Health Sciences Advisory Board, University of Illinois at Chicago, Chicago, Illinois, USA.*

Abstract

The purpose of this vision paper is to identify how data visualization could transform healthcare. Electronic Health Records (EHRs) are maturing with new technology and tools being applied. Researchers are reaping the benefits of data visualization to better access compilations of EHR data for enhanced clinical research. Data visualization, while still primarily the domain of clinical researchers, is beginning to show promise for other stakeholders. A non-exhaustive review of the literature indicates that respective to the growth and development of the EHR, the maturity of data visualization in healthcare is in its infancy. Visual analytics has been only cursorily applied to healthcare. A fundamental issue contributing to fragmentation and poor coordination of healthcare delivery is that each member of the healthcare team, including patients, has a different view. Summarizing all of this care comprehensively for any member of the healthcare team is a "wickedly hard" visual analytics and data visualization problem to solve.

Keywords:

Data Display, Data Mining, Electronic Health Records

Introduction

The role of electronic health records (EHRs) has been described as both transformative and turbulent [1]. There are even arguments as to whether an EHR can be considered disruptive technology (in the traditional marketplace sense without fundamental change in the healthcare business model [2]), or is simply found to be disruptive to clinicians [3].

No longer just for documentation and communication about individual patients among a local healthcare team, EHRs are intended to support improvement in the overall quality and cost of healthcare [4,5]. Today's EHRs are expected to improve access to data across the continuum of care – irrespective of organizational boundaries [6]. Despite problems with clinical decision support components [7,8], EHRs are also expected to aid evidence-based care using experiential data [9], social determinants of health as related to a given patient [10], and personally supplied health data [11] – none of which have heretofore been included in individual health records. And, when data analytics are available to a clinician (separate from or as a product of an EHR), they must supply evidentiary information in real, or near real time [12].

Significantly less has been written about the environment of use and human factors associated with use – especially cognitive performance [13] and associated workflows. Indeed, a *Journal of the American Medical Assocation (JAMA)* Viewpoint in 2016 [14] suggests that "the evolution of EHRs has not kept pace with technology widely used to track, synthesize, and visualize information in many other domains of modern life." There are a number of technologies that hold promise for improving the human experience in order to derive value from the EHR investment [15]. Some of these are older technologies, such as data display, registries, and registry functionality which typically have not been included in an EHR [16]. Some are newer, such as data/information visualization and visual analytics. The visual analytics discipline was initially founded in 2004 where the science of analytical reasoning with advanced interactive visual interfaces was challenged to analyze overwhelmingly disparate, conflicting, and dynamic information [17]. One of the earliest papers on visualization in healthcare for personal histories was published in 1996 [18].

In general, it is believed that the use of the term data visualization when applied in the literature to EHR systems is the result of a process of visual analytics. Data visualization may be static or interactive. When interactive, visual analytics supports the ability to act on the data in real time to glean additional perspectives. Interactive data visualization also puts control into the hands of the user, where details can be obtained 'on demand' [19]. Caban and Gotz [20] define visual analytics as "the science of analytical reasoning facilitated by advanced interactive visual interfaces." These authors go on to state that "visual analytics techniques combine concepts from data mining, machine learning, human computing interaction, and human cognition." This paper notes that "visual analytics systems – by combining advanced interactive visualization methods with statistical inference and correlation models – have the potential to support intuitive analysis for all … user populations while masking the underlying complexity of the data."[20] Finally, the statement made by Caban and Gotz that "the science of analytical reasoning facilitated by advanced interactive visual interfaces" makes the case for the authors to suggest that when a picture is worth a thousand words, data visualization is the picture created by a visual analytics technique applied to the thousand words [21]. The purpose of this paper is to provide a vision of data visualization's possibilities for leveraging new methodologies and techniques reflecting the diversity of health data and healthcare process.

Methods

A literature search was conducted using the terms data visualization and visual analytics focusing on real time or near real time EHR systems applied to clinical care. We also included the concepts of cognition or cognitive informatics. We avoided clinical decision support as too narrow, and description of tools without application to electronic health record data as too broad. The searches used PubMed. Due to the hybrid nature of visual analytics we also referred to a

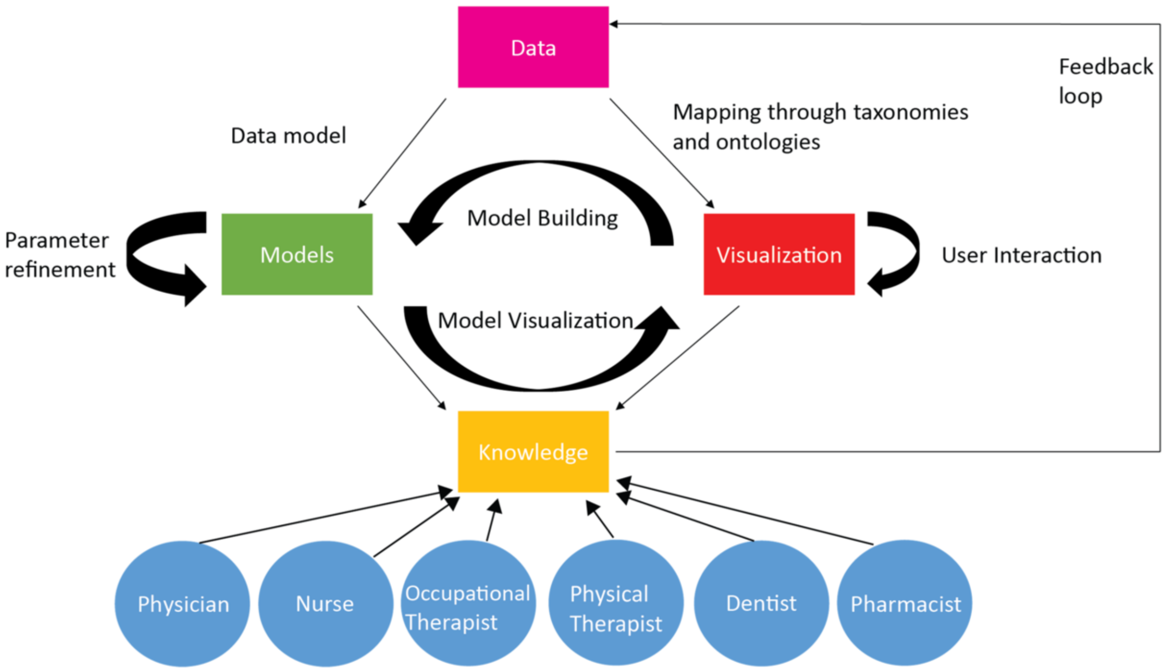

Figure 1 - Visual Data Exploration Inspired Across Muliple Health Disciplines adapted from Keim page 10 [19].

The bold contrasting colors between the data, models, knowledge, and visualization are designed to highlight the differences between the different areas of data exploration. The exploration begins with the data. The blue color of the health professional highlights the commonality of the biological underpinings of all health professionals, however each circle is distinct, as professional training is different. Professional input into the figure is through the knowledge obtained from the models as the preexisting clinical health model will be different for each profession and the knowledge obtained will be different. The thicker lines represent maunual steps through out the process, where the thin lines can become automated.

number of text books and design books focused on visual learning.

Data Visualization in the Electronic Health Record

A total of 19 papers were identified that included use cases for data visualization of EHR data.

Table 1 - Papers in Data visualization

Author	Use case
Basole [22]	Explore care processes for complex pediatric asthma patients in Emergency Department (ED).
Dolan [23]	Interactive decision dashboard to help patients make decisions about unfamiliar healthcare management strategies.
Evans [24]	Automated case detection and response triggering system to monitor non-Intensive Care Unit (ICU) hospitalized patients every 5 minutes and identify early stages of physiologic deterioration.
Faiola [25]	Dashboard via EHR combines data from bedside monitoring devices, EHR, and medication pump display in ICU to improve data retrieval.
Farri [26]	Visual cues in EHR document user interface to support discovery of relevant patient information.
Foraker [27]	On demand data visualization tool concurrent with EHR navigation triggers Application program interfaces (APIs) that collect parameters relative to cardiovascular health to render a risk profile for a given patient.
Hirsch [28]	Data visualization tool displays patient information on a timeline and a problem cloud to facilitate review of essential patient information.
Huang [29]	Visualization for temporal patterns of polymorbidities associated with complex chronic kidney disease (CKD) and its outcomes.
Huang [30] (Follow up study to [29])	Interactive web-based application enables researchers to study cohorts over time using EHR data; also can reveal potential trajectories of a disease over time.
Ledesma [31]	Visualization library studied on various usability tests that enabled users to understand health data and its evolution over time.
Militello [32]	Beta version of a screening and surveillance App (for colorectal cancer screening) used in the United States Veterans Health Administration's EHR.
Plaisant [33]	Assessed the effectiveness of a data visualization tool to improve the display of medication lists to be reconciled (upon discharge).
Radhakrishnan [34]	Use of visual analysis techniques to discover clinically salient associations between patient characteristics with problem-orient health outcomes of older adult home health patients during the home health service period.

Ratwani [35]	Intuitive visualization dashboards for end users to facilitate exploration of patient safety event reporting systems and analyze trends.
Simpao [36]	An alert dashboard was created using override rates to provide rapid-cycle safety information.
Soulakis [37]	Visualization of collaborative EHR usage for hospitalized patients with heart failure was used to help strategically guide care coordination for patients at risk for readmission.
Warner [38]	A visualization tool specifically designed to be accessible to clinicians enables exploring for "'patients like this one.'"
Wongsupha sawat [39]	Summarization of temporal event data extracted from EHRs of a cohort of patients can be used to analyze disease (congestive heart failure) progression pathways and their outcomes.
Wongsupha sawat [40]	Study of the use of a data visualization tool to describe event sequences in patient transfers between (ED, ICU, intermediate care, and hospital ward) departments.

Predominately, and not surprisingly, these use cases focused on what typically are described as high risk clinical scenarios – disease conditions associated with many co-morbidities and likelihood of emergency department use and hospital readmission, or chronic and debilitating conditions that generally lead to complications [41]. While these areas of focus are important, they are atypical and limited in applicability to the overall processes of healthcare delivery. Examples of chronic conditions in need of models include pediatric asthma, chronic kidney disease, heart failure, diabetes, multiple sclerosis, and depression. In addition, predictors for physiologic deterioration and cardiovascular health issues were geared toward maintaining a stable condition. Intensive Care Unit (ICU) data analysis, transfers among care sites, and medication reconciliation are all challenging issues in busy hospitals and frequently the cause of hospital-acquired conditions. Several of the papers identified suggested that there was not only time savings in clinicians attempting to look for 'patients like this one' [38] to make more informed diagnosis and/or treatment plans, but efforts to learn from other patient experiences were actually made wherein the past the time required would often have kept clinicians from conducting such an exercise at all. Although not explicitly stated in any of the papers reviewed, collectively there appears to be the suggestion that interaction with data visualization – which can take from 2 to 5 minutes according to several of the papers – is acceptable for complex clinical cases.

While the focus of the literature review was on use of data visualization in association with an EHR, which implies a healthcare encounter (i.e., hospitalization, emergency department service, or office/clinic visit), patients are increasingly interested in becoming involved in their care. Being able to present information to help patients make treatment choices or lifestyle changes in a manner that is accessible for patients can significantly aid consumer engagement in their care. However, to engage this the latent meaning in the health data need to become accessible to non-experts in biomedical science, i.e., the lay perspective. Through cognitively accessible data, patients can engage in meaningful interactions with health experts to clarify and to improve more rapidly with the goal to readily reduce the likelihood of acquiring or exacerbating a condition [42].

Interactive data

The prior data visualization papers did not always include an explicit model, how the data is interelated (Figure 1). Without models, data is just displayed and interaction is limited. The potential for various models to enable different filters to be applied based on the data needs of individual users or user types could allow a more interactive data presentation. It is well known that as many as a hundred different users may require access to a patient's health record in a hospital. The use of such modeling to create truly interactive visualization techniques in order to understand the clinical condition of the patient from any given perspective appears yet to have been addressed.

Imagine, for instance, a nutritionist's view of the patient's needs as they dynamically change based on the narrowing of the physician's differential diagnosis for the patient. One challenge unique to healthcare is that the knowledge base of professionals (physicians, nurses, social workers, pharmacists, physical therapists, occupational therapists, dentistry, nutritionist, public health and many more) is very broad. It appears that data visualization could be the means to aggregate and parse such massive knowledge bases by building models that support multivariate uses of data to improve the healthcare experience for patients.

Multivariate Datasets

Visualizing large continuous streams of structured data has been the focus to date, as described above. However, there are a number of other variables often not in such structured format. For example, lab values which arrive semiregularly can be updated as the results change from preliminary to final. Imaging modalities can vary from small size (amount of data) in data such as ultrasound, to the larger size in data including Magnetic Resonance Imaging, Computed tomography (CT), and many others. From all imaging modalities, the radiologist's interpretation is normally provided in free text. A common viewing technique is either one large table, or in a timeline based approach. The challenge with both is the user is required to model the information mentally to arrive at knowledge. Creativity of clinicians and visual artists is the only limiting factor in creating solutions to these challenges.

Another area of data that needs better modeling and visualization, is the critical thinking of all health professionals. Without visualizing how professionals' clinical judgement changes with new knowledge, continuously improving treatment protocols and impacting others' knowledge cannot be achieved.

Visual Thinking

Visual thinking is a way to organize your thoughts and simplify complex concepts. In figure 1, we show how data can be incorporated into both models and visualization to enable visual thinking. Through better models, we better understand the refinement needed to further make better models and incorporate them into better visualizations. The data needs to be mapped through taxonomies and ontologies (invisible to the end user) in order to improve visualization within the EHR that can impact how clinicians can visually think about data to aid healthcare. Users' interactions with visualization will create new knowledge. Just as knowledge is the application of experience to information, new knowledge will impact each professional based on personal experience. For example, an increase in a pain score (scale from 1 to 10) for a patient could indicate to a physician an additional medication may be needed, where the nurse may recognize the level of pain as a failure in pain management education, or a physical therapist may identify the pain as the result of a therapy session to increase range of motion. Depending on when the patient's pain score is assessed and the timing of how the three professionals interaction with the patient, all interpretations could be correct, only some could be correct, or none could be correct. Visualizing all of these interactions and building appropriate models across the range of disease states will be a challenge for the next decade. The creativity of the global community is required to solve hard challenges such as integrating multiple health professions into a single mutiprofessional intuative interface for something a common as a pain score and more innovation for the more complex health conditions encountered on a daily basis.

Designing new user interfaces for EHRs by applying these principles and new designs to engage clinicians both in the patient's working memory (part of short term memory that is concerned with immediate processing) and the health profressional's long term memory is a huge challenge. Data visualization design and conginive thought is not just about EHR usability criteria issued by United Statues National Institute of Standards and Technology (NIST). Rather, data visualization design and cognitive thought is about how healthcare professionals interact with the EHR. This paper focuses on a visual thinking process, and how the computer can engage both visual memory (a form of memory related to your visual experience) afforded through data visualization and working memory [43]. But even simple glyphs (icons), loaded with colors, shapes and direction, portray more information for working memory than just a list of data values. [43] For example, most EHR's list all of the laboratory values as simple numbers on a table. Applying these principals to ordinary laboratory results could improve time and comprehension of these data.

Discussion

The design and artistic thought and expression of models, visualization, and existing knowledge are not incorporated into the current EHRs. With better models of the clinical decision making of health professionals, the data becomes more amenable to visualizations. Through better measurement and representation, deeper knowledge about the patients and the work flow processes can be studied and improved. Through visual thinking research, refinement of the models, and collaboration with biomedical illustrators, a more intuitive and dynamic interface can enable clinicians to treat patients instead of spending hours reading computer screens.

Conclusions

The maturity of data visualization in healthcare is in its infancy. Visual analytics has been only cursorily applied to the healthcare field. Healthcare is one of the most complex of all disciplines, reflecting a diversity of trained professional team members in the care of an individual patient. For example, a single patient could encounter in one hospitalization, several different physicians, nurses, pharmacists, social workers, hospital administrators, physical therapists, occupational therapists, respiratory therapists, lab technicians, and many others. Each professional has a different view of the patient, and everyone contributes to the care of the patient differently. Through visual thinking and models new interactions with the EHR can improve speed of consuming information and memory. Arming these professionals and the patients themselves with visual thinking is a "wickedly hard" problem to solve. As the fields of visual analytics and data visualization mature, the design criteria and improved usability will help improve the treatment of patients.

Acknowledgements

We would like to thank Mika Ishikawa, student in Health Information Management at the UIC, and Claire Heshmat, student in Biology at the UIC, for their assistance in conducting the literature search.

References

[1] VL Patel, TG Kannampallil. Cognitive informatics in biomedicine and healthcare, *J Biomed Inform* 53 (2015), 3-14.

[2] Wananmaker B, Bean D,. Why EHRs are not (yet) disruptive. 2013; Available at: https://www.christenseninstitute.org/blog/why-ehrs-are-not-yet-disruptive/. Accessed April 6th, 2017.

[3] AK Jha, D Doolan, D Grandt, T Scott, DW Bates. The use of health information technology in seven nations, *Int J Med Inform* 77 (2008), 848-854.

[4] A Sheikh, HS Sood, DW Bates. Leveraging health information technology to achieve the "triple aim" of healthcare reform, *J Am Med Inform Assoc* 22 (2015), 849-856.

[5] JR Windle, TA Windle. Electronic Health Records and the Quest to Achieve the "Triple Aim", *J Am Coll Cardiol* 65 (2015), 1973-1975.

[6] B Bell, K Thornton. From promise to reality: achieving the value of an EHR, *Healthc Financ Manage* 65 (2011), 50-56.

[7] DL Hunt, RB Haynes, SE Hanna, K Smith. Effects of computer-based clinical decision support systems on physician performance and patient outcomes: a systematic review, *JAMA* 280 (1998), 1339-1346.

[8] A Wright, TT Hickman, D McEvoy, S Aaron, A Ai, JM Andersen, et al. Analysis of clinical decision support system malfunctions: a case series and survey, *J Am Med Inform Assoc* 23 (2016), 1068-1076.

[9] T Greenhalgh, J Howick, N Maskrey, Evidence Based Medicine Renaissance Group. Evidence based medicine: a movement in crisis? *BMJ* 348 (2014), g3725.

[10] Committee on the Recommended Social and Behavioral Domains and Measures for Electronic Health Records, Board on Population Health and Public Health Practice, Institute of Medicine. (2014).

[11] AE Chung, EM Basch. Incorporating the patient's voice into electronic health records through patient-reported outcomes as the "review of systems", *J Am Med Inform Assoc* 22 (2015), 914-916.

[12] W Raghupathi, V Raghupathi. Big data analytics in healthcare: promise and potential, *Health Inf Sci Syst* 2 (2014), 3-2501-2-3. eCollection 2014.

[13] RJ Holden. Cognitive performance-altering effects of electronic medical records: An application of the human factors paradigm for patient safety, *Cogn Technol Work* 13 (2011), 11-29.

[14] DM Zulman, NH Shah, A Verghese. Evolutionary Pressures on the Electronic Health Record: Caring for Complexity, *JAMA* 316 (2016), 923-924.

[15] L Riskin, R Koppel, D Riskin. Re-examining health IT policy: what will it take to derive value from our investment? *J Am Med Inform Assoc* 22 (2015), 459-464.

[16] AS O'Malley, K Draper, R Gourevitch, DA Cross, SH Scholle. Electronic health records and support for primary care teamwork, *J Am Med Inform Assoc* 22 (2015), 426-434.

[17] Thomas, J. J., Cook, Kristin A.,National Visualization and Analytics Center.,. *Illuminating the path.* : IEEE Computer Society Los Alamitos, Calif., 2005.

[18] LifeLines: visualizing personal histories. Proceedings of the SIGCHI conference on Human factors in computing systems: ACM; 1996.

[19] D Keim, F Mansmann, J Schneidewind, J Thomas, H Ziegler. Visual analytics: Scope and challenges, *Visual data mining* (2008), 76-90.

[20] JJ Caban, D Gotz. Visual analytics in healthcare--opportunities and research challenges, *J Am Med Inform Assoc* 22 (2015), 260-262.

[21] Forum One Communications. Worht a Thousand Words: How to Display Health Data. 2014; Available at: http://www.chcf.org/publications/2014/02/worth-thousand-words-data. Accessed April/17, 2017.

[22] RC Basole, ML Braunstein, V Kumar, H Park, M Kahng, DH Chau, et al. Understanding variations in pediatric asthma care processes in the emergency department using visual analytics, *J Am Med Inform Assoc* 22 (2015), 318-323.

[23] JG Dolan, PJ Veazie, AJ Russ. Development and initial evaluation of a treatment decision dashboard, *BMC Med Inform Decis Mak* 13 (2013), 51-6947-13-51.

[24] RS Evans, KG Kuttler, KJ Simpson, S Howe, PF Crossno, KV Johnson, et al. Automated detection of physiologic deterioration in hospitalized patients, *J Am Med Inform Assoc* 22 (2015), 350-360.

[25] A Faiola, P Srinivas, J Duke. Supporting Clinical Cognition: A Human-Centered Approach to a Novel ICU Information Visualization Dashboard, *AMIA Annu Symp Proc* 2015 (2015), 560-569.
[26] O Farri, A Rahman, KA Monsen, R Zhang, SV Pakhomov, DS Pieczkiewicz, et al. Impact of a prototype visualization tool for new information in EHR clinical documents, *Appl Clin Inform* 3 (2012), 404-418.
[27] RE Foraker, B Kite, MM Kelley, AM Lai, C Roth, MA Lopetegui, et al. EHR-based Visualization Tool: Adoption Rates, Satisfaction, and Patient Outcomes, *EGEMS (Wash DC)* 3 (2015), 1159-9214.1159. eCollection 2015.
[28] JS Hirsch, JS Tanenbaum, S Lipsky Gorman, C Liu, E Schmitz, D Hashorva, et al. HARVEST, a longitudinal patient record summarizer, *J Am Med Inform Assoc* 22 (2015), 263-274.
[29] CW Huang, S Syed-Abdul, WS Jian, U Iqbal, PA Nguyen, P Lee, et al. A novel tool for visualizing chronic kidney disease associated polymorbidity: a 13-year cohort study in Taiwan, *J Am Med Inform Assoc* 22 (2015), 290-298.
[30] CW Huang, R Lu, U Iqbal, SH Lin, PA Nguyen, HC Yang, et al. A richly interactive exploratory data analysis and visualization tool using electronic medical records, *BMC Med Inform Decis Mak* 15 (2015), 92-015-0218-7.
[31] A Ledesma, M Al-Musawi, H Nieminen. Health figures: an open source JavaScript library for health data visualization, *BMC Med Inform Decis Mak* 16 (2016), 38-016-0275-6.
[32] LG Militello, JJ Saleem, MR Borders, CE Sushereba, D Haverkamp, SP Wolf, et al. Designing Colorectal Cancer Screening Decision Support: A Cognitive Engineering Enterprise, *J Cogn Eng Decis Mak* 10 (2016), 74-90.
[33] C Plaisant, J Wu, AZ Hettinger, S Powsner, B Shneiderman. Novel user interface design for medication reconciliation: an evaluation of Twinlist, *J Am Med Inform Assoc* 22 (2015), 340-349.
[34] K Radhakrishnan, KA Monsen, SH Bae, W Zhang. Visual Analytics for Pattern Discovery in Home Care. Clinical Relevance for Quality Improvement, *Appl Clin Inform* 7 (2016), 711-730.
[35] RM Ratwani, A Fong. 'Connecting the dots': leveraging visual analytics to make sense of patient safety event reports, *J Am Med Inform Assoc* 22 (2015), 312-317.
[36] AF Simpao, LM Ahumada, BR Desai, CP Bonafide, JA Galvez, MA Rehman, et al. Optimization of drug-drug interaction alert rules in a pediatric hospital's electronic health record system using a visual analytics dashboard, *J Am Med Inform Assoc* 22 (2015), 361-369.
[37] ND Soulakis, MB Carson, YJ Lee, DH Schneider, CT Skeehan, DM Scholtens. Visualizing collaborative electronic health record usage for hospitalized patients with heart failure, *J Am Med Inform Assoc* 22 (2015), 299-311.
[38] JL Warner, JC Denny, DA Kreda, G Alterovitz. Seeing the forest through the trees: uncovering phenomic complexity through interactive network visualization, *J Am Med Inform Assoc* 22 (2015), 324-329.
[39] Outflow: Visualizing patient flow by symptoms and outcome. IEEE VisWeek Workshop on Visual Analytics in Healthcare, Providence, Rhode Island, USA: American Medical Informatics Association; 2011.
[40] LifeFlow: visualizing an overview of event sequences. Proceedings of the SIGCHI conference on human factors in computing systems: ACM; 2011.
[41] S Howell, M Coory, J Martin, S Duckett. Using routine inpatient data to identify patients at risk of hospital readmission, *BMC Health Serv Res* 9 (2009), 96-6963-9-96.
[42] J Laurance, S Henderson, PJ Howitt, M Matar, H Al Kuwari, S Edgman-Levitan, et al. Patient engagement: four case studies that highlight the potential for improved health outcomes and reduced costs, *Health Aff (Millwood)* 33 (2014), 1627-1634.
[43] Ware C,. Information visualization : perception for design. Morgan Kaufmann (Elsevier) Boston, MA, 2013.

Address for correspondence

Andrew D. Boyd (boyda@uic.edu) 1919 W Taylor St. MC 530 Chicago, IL 60612, USA. +1 (312) 996-8339.