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CASE STUDY

Improving the Efficiency and Ease of Healthcare Analysis Through Use of Data Visualization Dashboards

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Abstract

The digitization of a patient's health record has profoundly impacted medicine and healthcare. The compilation and accessibility of medical history has provided clinicians an unprecedented, holistic account of a patient's conditions, procedures, medications, family history, and social situation. In addition to the bedside benefits, this level of information has opened the door for population-level monitoring and research, the results of which can be used to guide initiatives that are aimed at improving quality of care. Cerner Corporation partners with health systems to help guide population management and quality improvement projects. With such an enormous and diverse client base—varying in geography, size, organizational structure, and analytic needs—discerning meaning in the data and how they fit with that particular hospital's goals is a slow, difficult task that requires clinical, statistical, and technical literacy. This article describes the development of dashboards for efficient data visualization at the healthcare facility level. Focusing on two areas with broad clinical importance, sepsis patient outcomes and 30-day hospital readmissions, dashboards were developed with the goal of aggregating data and providing meaningful summary statistics, highlighting critical performance metrics, and providing easily digestible visuals that can be understood by a wide range of personnel with varying levels of skill and areas of expertise. These internal-use dashboards have allowed associates in multiple roles to perform a quick and thorough assessment on a hospital of interest by providing the data to answer necessary questions and to identify important trends or opportunities. This automation of a previously manual process has greatly increased efficiency, saving hours of work time per hospital analyzed. Additionally, the dashboards have standardized the analysis process, ensuring use of the same metrics and processes so that overall themes can be compared across hospitals and health systems.

Key words: big data analytics; business intelligence; data distribution; healthcare; structured data

Introduction

The federal push for Electronic Health Record adoption, highlighted by the 2009 Health Information Technology for Economic and Clinical Health Act (HITECH ACT) allocating $19.2 billion to increase electronic health record (EHR) use, has led to a dramatic increase in the amount and availability of digital healthcare data.[1,2] Spanning the range of a patient's encounter (vitals, labs, diagnoses, procedures, medications, etc.), while also providing historical context (medical, family, and social history), data contained within the EHR can paint a robust picture of a single visit, or longitudinal medical history. Further, the ability exists to zoom out and view higher-level summaries of a patient population (specific condition or procedure group), unit (medical floor, ICU), facility, or entire health system. Therein lies both the promise and the problem of electronic medical data. The potential impact of the data is exceptional. Studied and applied appropriately, it can be transformative–guiding quality improvement, establishing best practice standards, and identifying opportunities for improvement. As stated by Murdoch and Detsky:

"The first information technology revolution in medicine was the digitization of the medical record. The second is surely to leverage the information contained therein and combine it with other sources. Big data has the potential to transform medical practice by using

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information generated every day to improve the quality and efficiency of care."[2]

However, the abundance of data can be overwhelming. Utility is easily masked by the noise of numbers, and the time required to mine for value can be prohibitive. Further, although long-term analysis is important, use of EHR data for daily analysis is critical. The clinician's immediate concern is often current performance, and how that compares with the previous week or month, and not the big analytics picture. This concern is well founded, as daily clinical processes determine the success or failure of improvement initiatives.

Removal of the limitation of being bound by a particular facility or system opens another avenue of cross-facility data exploration and allows the use of trends comparatively, adding an industry-wide context to any analysis or findings. However, this additional layer, while increasing the possible breadth and depth of insight, also increases the complexity of analysis and understanding. Humans have a limited capacity to process information, and without proper tools, as complexity increases, accuracy of interpretation decreases.[3] The amount of data contained within the EHR raises the possibility of overlooking or misinterpreting the value within the data.

One powerful option by which complex data could be made accessible, consumable, and meaningful is through the use of interactive visualizations.[4,5] The field of data visualization has experienced tremendous growth as multiple industries have attempted to harness the power of big data.[6] The goal is to produce easily understood visuals to aid the users' ability to quickly and accurately process information so that conclusions can be drawn, decisions made, and actions taken. Although the popularity of dashboards as analytic tools is growing, their use with EHR data is still in its infancy.[7,8] Certainly, some healthcare organizations utilize EHR data, along with other sources, in dashboards to monitor performance at the individual facility or system level.[9,10] And most literature in the field centers on reviewing the current state or discussing the potential of EHR data visualization.[7,8,11,12] Few studies exist, however, detailing the creation, use, and benefits of EHR data visualizations.[13–15] One possible explanation could simply be the immense volume of data within the EHR.[16] Summarizing all the important information, even visually, is impossible; therefore, decisions about priority of information must be made.

Two common concerns for health systems are early identification and treatment of sepsis, and prevention of 30-day hospital readmissions. Sepsis is a systemic inflammatory response to infection, which can progress to severe sepsis (sepsis with organ dysfunction) or septic shock (severe sepsis plus hypotension that persists after fluid resuscitation).[17,18] Sepsis incidence is on the rise, and detection, while improving, remains challenging.[19] Further, sepsis is an incredibly costly disease. From the patient side, mortality rates for severe sepsis and septic shock range from 20% to 50%,[17,18] and survivors often experience a decreased quality of life.[20] On the caregiver side, sepsis can account for up to 50% of all hospital deaths[21] and is the most expensive condition treated in U.S. hospitals.[22] Numerous studies have examined the impact of sepsis treatment on patient outcomes,[23,24] and the Surviving Sepsis Campaign publishes evidence-based best practices,[25] which are time sensitive, in an effort to halt disease progression.

Similar to sepsis, 30-day hospital readmissions are a measure reported to CMS. Hospitals with excessive readmission rates for select conditions/procedures face penalties.[26] In response, many hospitals have developed readmission prevention programs, dedicating resources to improving discharge processes.[27–29] More than half of U.S. hospitals were penalized and will see a reduction in payment for every re-hospitalized Medicare patient in 2016, losing a combined $420 million.[30]

Clinical decision support (CDS) systems leverage EHR data and algorithms to aid in identification and management of patients at elevated risk for adverse outcomes. Focusing on the process and outcome measures associated with a particular CDS system allows creation of dashboards around important safety measures. Early sepsis recognition systems use EHR data to identify patients meeting the criteria for systemic inflammatory response syndrome and alert caregivers. These systems have benefited early identification of sepsis and patient outcomes.[31–33] Similarly, readmission risk prediction algorithms use EHR data elements to predict a patient's likelihood of returning to the hospital within 30 days.[34]

Here, we describe the creation and use of two separate EHR data dashboards that allow robust visualizations of the processes and outcomes associated with sepsis and 30-day readmissions for hospitals using Cerner Corporation's CDS systems (St. John Sepsis Agent and All-Cause Readmission Prevention). The goal is to use these dashboards for data monitoring and analysis of hospitals both individually and as a group. Although the decisions produced by an analysis will vary by each healthcare facility's specific circumstances and environment, common goals include identifying quality improvement, progress in patient outcomes, and the need for further optimization. However, the results of the analysis are outside the scope of this work. Thus, we compare time spent building, maintaining, and using these dashboards with the time required for the traditional manual data analysis to assess the impact of the visualization tools. Finally, we discuss how these results will guide future analytics developments.

Materials and Methods

Dashboard design

The designs of the dashboards need to accomplish three broad goals: increasing efficiency while decreasing variability of the analysis process, meeting the needs of the analytics team (analysts, data scientists) while being accessible to a range of diverse users (clinical, administration, IT, business, etc.), and accommodating any hospital's EHR data.

Although the ultimate goal is to have a dashboard for a variety of CDS systems, sepsis and readmission prevention were chosen first. This decision was based on the level of burden to health systems, complexity and time of analysis, and requests from potential dashboard users. Working with project leaders and consultants, and drawing from previous analyses, we identified the most valuable metrics to evaluate outcomes and processes related to sepsis and readmission prevention. For sepsis, these measures included sepsis incidence, length of stay, and mortality rate. For readmissions, we developed process metrics related to the CDS system, which were risk stratifications of the target population, plans of care initiated, and follow-up appointments scheduled. New metrics were not defined for either dashboard. Our intent was to automate the aggregation and visualization of the same metrics that analysts are consistently utilizing so that similar conclusions can be drawn in a more timely manner.

These key indicators were defined in requirements documents, and user input helped identify what types of visualizations would be the most meaningful. We created several visual representations of each metric, aiming at displaying the information in one to two views to minimize navigation and clicks. Further, metrics were visualized across the months for which historical data were available, as identifying trends and anomalies in data are important to end-users. Multiple versions of the dashboards were developed, tested, and revised before release to a select number of consultants. These consultants used the dashboards for data monitoring and provided feedback in bi-weekly review sessions. Their feedback (i.e., identifying missing data and color, font, and sizing changes) was incorporated before releasing the dashboards to the broader consulting group.

Before these dashboards, the analytics teams manually queried, cleaned, aggregated, and analyzed data one facility at a time. An analyst accessed and extracted readmissions or sepsis data in 1-month increments. Data were then aggregated and cleaned in R before exporting to an Excel workbook where pivot tables and graphs were created to calculate and visualize each metric. By standardizing the analysis, variability in metric definition and user errors during data aggregation and cleaning are eliminated.

Dashboard development and maintenance

In contrast to manual extractions from individual facilities, the dashboards utilize Tableau visualization software and aggregated hospital-level data from a cloud platform. Once education from the database architects on the existing summary tables was complete, the team began extracting data and continues to do so on a monthly basis. Extractions rely on SQL queries, and the resulting data are then formatted into comma separated values that can be consumed by Tableau.

The source data described earlier were merged with data from a project tracking source where CDS system implementation dates are stored. The dashboards include pre- and post-implementation assessments of key metrics to identify improvements in processes and patient outcomes.

Dashboards are maintained through an automated process. The team executes the SQL query monthly, pulling data across facilities, and these data are added to a master file connected to Tableau. The extracts in Tableau are refreshed, and data of all facilities are updated and available to end-users. When new facilities implement the CDS systems, data are automatically added to the cloud tables and the monthly data extraction. The views are housed in an internal server that associates various roles that one can have access to.

Efficiency and time savings calculations

To estimate time savings, we calculated the average amount of time spent on manual analyses of sepsis and readmissions and determined how many clients are included in the two dashboards. We gauged how many clients are analyzed annually and multiplied that number of clients by the number of hours allotted for the analyses. From this value, we subtracted the number of hours that the team spends on dashboard development and maintenance and the time spent on review and interpretation with project teams. We calculated time savings for year 1, when the dashboards were developed, and projected time savings for years 2 and 3.

The current number of clients in the dashboards was utilized for year 1. For future years, we conservatively projected how many clients would be added to the dashboards in years 2 and 3. These projections are based on the numbers of clients who have implemented the two CDS systems in past years. Annually, the analytics team is responsible for analyzing the data of ~40% of all sepsis clients and ~65% of all readmissions clients. Analysis rates were calculated from data analysis tracking records, which have been maintained during the last 6 months of 2015. The raw number of client analyses was summed and annualized, and the rate was applied to the number of clients in each of the dashboards.

The following formula was utilized to determine time savings:

$$\textit{Total Hours Saved} = ((\textit{Total Number of Clients} * \textit{Rate of Clients Analyzed}) * \textit{Average Manual Analysis Hours per Client}) - (\textit{Development and Maintenance} + \textit{Review and Interpration}))$$

Finally, we utilized a two-sample t-test to determine any statistically significant differences between the time spent per client project on manual analysis and the automated process via the two dashboards. We calculated the average amount of time to conduct a manual analysis using internal tracking data on manual analyses completed in 2015. To calculate the average time spent per project in the new method, for each dashboard, we divided the number of hours used for dashboard development and maintenance by the number of clients analyzed annually.

Results

Development and utilization of these dashboards has resulted in significant time savings. What was previously manual, completed on an *ad hoc* basis for one client at a time, has now been converted into a central resource where analysis of many clients' data is readily available to end-users.

For sepsis outcomes, this work required one analyst to spend ~5 hours gathering and analyzing data from one average-sized client, plus around 1 hour reviewing results with the project team. For readmissions outcomes, this work required ~4 hours, including 3 hours of analysis and 1 hour of review.

For year 1, we subtracted time for dashboard development, which was ~25 hours for each dashboard. Also in year 1, we added time for dashboard maintenance, which was ~12 hours for the sepsis dashboard and 5 hours for the readmissions dashboard. To calculate savings for future years, we subtracted time for dashboard maintenance, ~2 hours per month, resulting in 24 hours annually per dashboard. Because the team continues to consult on the dashboards and reviews results with project teams, we also subtracted the amount of time spent on those activities from overall time savings calculations. Collectively, we spend around 10 hours per month working with project teams on sepsis outcomes and 4 hours per month on readmissions outcomes.

Within the sepsis dashboard in year 1, there were 1389 total facilities across 186 clients. The team analyzes around 40% of sepsis clients annually, which was 74 clients in year 1. Using the manual process, the analytics teams spent ~446 hours analyzing sepsis outcomes across clients in year 1 (74 clients multiplied by 6 hours). After subtracting the hours for dashboard development and maintenance (37 hours in year 1) and reviewing the dashboard internally (120 hours annually), ~289 hours were saved in year 1 (Table 1). We project that in years 2 and 3, we will save ~326 and 350 hours, respectively. When compared with the manual sepsis analysis process, the time spent per client project has been reduced significantly, $t(73) = 4.97$, $p < 0.001$.

The readmissions dashboard is smaller and less established than the sepsis outcomes dashboard. Within the readmissions dashboard in year 1, there

Table 1. Time savings calculations from sepsis dashboard development

	Year 1	*Year 2*	*Year 3*
Sepsis dashboard			
Number of clients in dashboard	186	196	206
Clients analyzed on annual basis (40%)	74	78	82
Average hours per client—manual process	6	6	6
Manual analysis—total hours	446	470	494
Dashboard development and maintenance	(37)	(24)	(24)
Project team review of dashboard and interpretation	(120)	(120)	(120)
Total time savings (in hours)	289	326	350

Table 2. Time savings calculations from readmissions dashboard development

	Year 1	*Year 2*	*Year 3*
Readmissions dashboard			
Number of clients in dashboard	18	42	66
Clients analyzed on annual basis (65%)	12	27	43
Average hours per client—manual process	4	4	4
Manual analysis—total hours	47	109	172
Dashboard development and maintenance	(30)	(24)	(24)
Project team review of dashboard and interpretation	(48)	(48)	(48)
Total time savings (in hours)	0	37	100

were 47 facilities across 18 clients. The team analyzes ~65% of these clients annually, around 12 clients. Using the manual process, the team spent 48 hours analyzing readmissions outcomes in year 1 (12 clients multiplied by 4 hours). After subtracting the hours for dashboard development and maintenance (30 hours in year 1) and reviewing and interpreting the dashboard internally (48 hours annually), there were no significant time savings in year 1. However, as the dashboard expands with more clients, we project that in years 2 and 3, we will save ~37 and 100 hours, respectively (Table 2). When compared with manual readmissions analysis, the time spent per client project has been reduced significantly using this dashboard, $t(17) = 2.16$, $p < 0.05$.

Utilization of data visualizations has resulted in significant time savings for the analytics team. Between the two dashboards, we estimate a total of 289 hours saved in year 1, and project savings of ~364 hours in year 2 and 450 hours in year 3. Assuming a 40-hour workweek, these time savings translate to approximately seven full weeks of work in year 1, 9 weeks in year 2, and 11 weeks in year 3 (Table 3).

Discussion and Conclusions

This work demonstrates that interactive data visualizations can optimize data analysis in healthcare IT. The dashboards described (Figs. 1 and 2) have almost completely eliminated the need for time-consuming manual analyses of sepsis and readmissions data. Although the metrics monitored using the dashboards are the same as those of the previous manual evaluation, we have standardized the analysis to reduce variability and error across projects. Further, the dashboards have enabled a broader range of end-users to access data and gather insights. Consultants with clinical backgrounds now have a clear understanding of the metrics, their definitions and interpretations without direct support from the analytics team. Project teams also benefit, as they have complex data analysis and results are readily available.

Although similar EHR dashboards exist at individual healthcare facilities, important differences set apart the work described here. Though helpful, localized efforts produce disparate visualizations that are unique to the institutions that created them. This makes comparisons difficult and limits the scope of analysis. The visualizations described here can be used to analyze a single facility, or for a comparative analysis across numerous facilities. This ensures scalability, as future hospitals using the sepsis or readmission prevention CDS systems will be added to the dashboards to increase the already large data pool. In addition, we present real increases in efficiency and weeks of time saved by using dashboards instead of the previous manual analyses.

These dashboards have accomplished the goals of increasing the speed and consistency of analysis, but the work described here is evaluating only part of the process. The aim was not to change the conclusions reached and decisions produced from the analysis. Our hypothesis is that decision making either has not changed, in cases where the analytics team was providing the same metrics manually, or has improved, in cases where data were not used or were inaccurate but are now more accessible and reliable. However, this was not evaluated in the present study, and more work is needed to fully understand the impact of dashboards on decisions made based on the data.

The lessons learned and benefits from these visualizations can now be translated across other areas of healthcare and technology. Data cleaning and aggregation across many facilities posed significant challenges in this process. The finished product, however, outweighed these challenges, as we were able to leverage the data easily for visualizations and utilize similar data structures for other projects. Additionally, project teams and key stakeholders needed requisite education on utilizing these two dashboards, and appropriate collateral and

Table 3. Cumulative time savings from development of sepsis and readmissions dashboards

	Year 1	*Year 2*	*Year 3*
Total time savings			
Total time savings—Sepsis dashboard	289	326	350
Total time savings—Readmissions dashboard	0	37	100
Cumulative hours saved	289	364	450
Cumulative weeks of work saved[a]	7	9	11

[a]Assumes a 40-hour workweek.

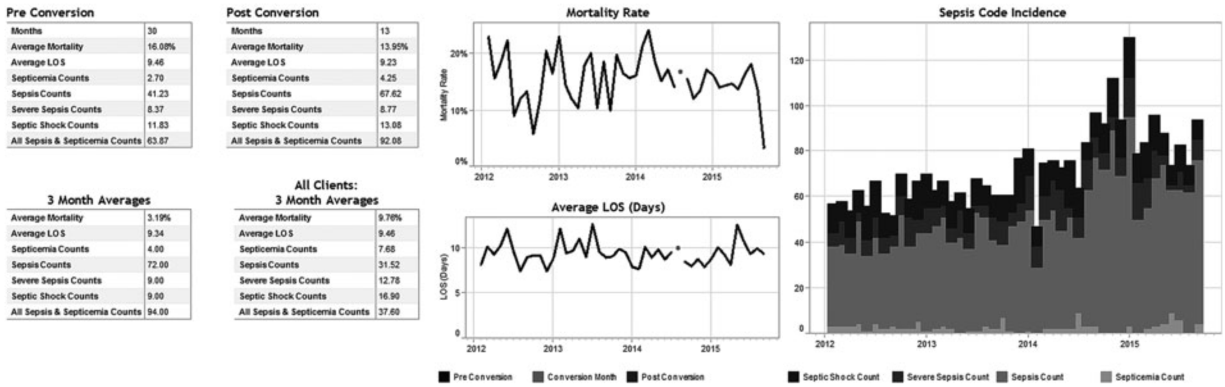

FIG. 1. This sepsis outcomes dashboard gives users a concise view of the clients' key performance indicators. The dashboard shows mortality rate, length of stay, and sepsis coding by month, along with a 3-month rolling average across all clients in the dashboard.

documentation still require improvement as the dashboards are released to more users. This work requires input from multiple roles and team members, and we continue to optimize the process of using more automatic analyses within our organization.

The two dashboards described within this article solve only a small portion of data science problems within the field. These dashboards make complex healthcare data on sepsis and readmissions more accessible, consumable, and meaningful to stakeholders, who can now more easily understand and interpret results for their clients. More development and research on the benefits of data visualization in healthcare is needed, but our efforts illustrate that substantial time savings are possible and the world of data analysis can be opened to many roles outside of analytics teams.

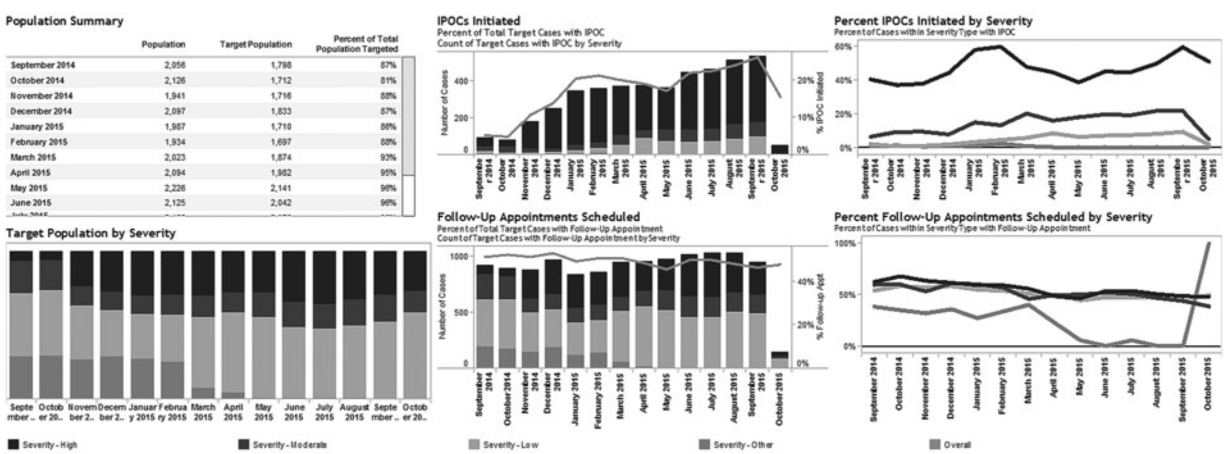

FIG. 2. This 30-day readmissions dashboard gives users the ability to view summaries and trends in their clients' populations. Combinations of column and line charts display the percentages of interdisciplinary plans of care and follow-up appointments scheduled in comparison to the number of readmissions cases, each broken down by predicted risk severity.

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Author Disclosure Statement

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References

1. Data Show Electronic Health Records Empower Patients and Equip Doctors. 2013. Available online at https://cms.gov/newsroom/mediareleasedatabase/press-releases/2013-press-releases-items/2013-07-17.html (last accessed December 22, 2015).
2. Murdoch TB, Detsky AS. The inevitable application of big data to health care. JAMA. 2013;309:1351–1352.
3. Halford GS, Baker R, Mccredden JE, Bain JD. How many variables can humans process? Psychol Sci. 2005;16:70–76.
4. Thomas JA, Cook KA. Illuminating the path: The research and development agenda for visual analytics. IEEE Comput Soc. 2005;54:184.
5. Kielman J, Thomas J, May R. Foundations and frontiers in visual analytics. Inf Vis. 2009;8:239–246.
6. Thomas J, Kielman J. Challenges for Visual Analytics. Inf Vis. 2009;8:309–314.
7. West VL, Borland D, Hammond WE. Innovative information visualization of electronic health record data: A systematic review. J Am Med Inform Assoc. 2015;22:330–339.
8. Caban JJ, Gotz D. Visual analytics in healthcare—opportunities and research challenges. J Am Med Inform Assoc. 2015;22:260–262.
9. Weiner J, Balijepally V, Tanniru M. Integrating strategic and operational decision making using data-driven dashboards: The Case of St. Joseph Mercy Oakland Hospital. J Healthc Manag. 2015;60:319–330.
10. Wyatt J. Scorecards, dashboards, and KPIs keys to integrated performance measurement. Healthc Financ Manag. 2004;58:76–80.
11. Zhang X, Gallagher K, Goh S. BI APPLICATIONS FOR HEALTHCARE. In: AMCIS 2011 Proceedings - All Submissions. Paper 442. Available online at http://aisel.aisnet.org/amcis2011_submissions/442 (last accessed December 22, 2015).
12. Shneiderman B, Plaisant C, Hesse BW. Improving health and healthcare with interactive visualizaiton methods. HCIL Tech Rep. 2013;1:1–13.
13. Dowding D, Randell R, Gardner P, et al. Dashboards for improving patient care: Review of the literature. Int J Med Inform. 2015;84:87–100.
14. Shaw S, Jacobs B, Stockwell D, et al. Effect of a real-time pediatric ICU safety bundle dashboard on quality improvement measures. Jt Comm J Qual Patient Saf. 2015;41:414–420.
15. Pageler N, Longhurst C, Wood M, et al. Use of electronic medical record-enhanced checklist and electronic dashboard to decrease CLABSIs. Pediatrics. 2014;133:738–746.
16. Sullivan & Frost. Drowning in Big Data? Reducing Information Technology Complexities and Costs For Healthcare Organizations. Available online at https://emc.com/collateral/analyst-reports/frost-sullivan-reducing-information-technology-complexities-ar.pdf (last accessed December 23, 2015).
17. Angus DC (Pitt), van der Poll T. Severe sepsis and septic shock. N Engl J Med. 2013;369:840–851.
18. Mayr FB, Yende S, Angus DC. Epidemiology of severe sepsis. Virulence. 2014;5:4–11.
19. Kumar G, Kumar N, Taneja A, et al. Nationwide trends of severe sepsis in the 21st century (2000–2007). Chest. 2011:1223–1231.
20. Gallop KH, Kerr CEP, Nixon A, et al. A qualitative investigation of patients' and caregivers' experiences of severe sepsis. Crit Care Med. 2015;43:296–307.
21. Liu V, Escobar GJ, Greene JD, et al. Hospital deaths in patients with sepsis from 2 independent cohorts. JAMA. 2014;312:90–92.
22. The Top Five Most Expensive Conditions Treated in U.S. Hospitals. 2011. Available online at http://hcup-us.ahrq.gov/reports/statbriefs/statbriefs.jsp (last accessed December 23, 2015).
23. Martin-loeches I, Levy MM, Artigas A. Management of severe sepsis: Advances, challenges, and current status. Drug Des Devel Ther. 2015;9:2079–2088.
24. Cawcutt KA, Peters SG. Severe sepsis and septic shock: Clinical overview and update on management. Mayo Clin Proc. 2014;89:1572–1578.
25. Dellinger RP, Levy MM, Opal SM, et al. Surviving sepsis campaign: International guidelines for management of severe sepsis and septic shock, 2012. Intensive Care Med. 2013;39:165–228.
26. CMS.gov Readmissions Reduction Program. Available online at https://cms.gov/medicare/medicare-fee-for-service-payment/acuteinpatientpps/readmissions-reduction-program.html (last accessed December 23, 2015).
27. Leppin AL, Gionfriddo MR, Kessler M, et al. Preventing 30-day hospital readmissions a systematic review and meta-analysis of randomized trials. JAMA Intern Med. 2014;55905:1095–1107.
28. Cavanaugh JJ, Jones CD, Embree G, et al. Implementation science workshop: Primary care-based multidisciplinary readmission prevention program. J Gen Intern Med. 2014;29:798–804.
29. Costantino ME, Frey B, Hall B, Painter P. The influence of a postdischarge intervention on reducing hospital readmissions in a medicare population. Popul Health Manag. 2013;16:310–316.
30. Rau J. 2015. Half of Nation's Hospitals Fail Again To Escape Medicare's Reamdission Penalties. Available online at http://khn.org/news/half-of-nations-hospitals-fail-again-to-escape-medicares-readmission-penalties (last accessed December 22, 2015).
31. Amland RC, Hahn-Cover KE. Clinical decision support for early recognition of sepsis. Am J Med Qual. 2016;31:103–110.
32. Amland RC, Haley JM, Lyons JJ. A multidisciplinary sepsis program enabled by a two-stage clinical decision support system: Factors that influence patient outcomes. Am J Med Qual. 2015 [Epub ahead of print]; DOI: 10.1177/1062860615606801
33. Amland RC, Lyons JJ, Greene TL, Haley JM. A two-stage clinical decision support system for early recognition and stratification of patients with sepsis: An observational cohort study. JRSM Open. 2015;6:1–10.
34. Choudhry SA, Li J, Davis D, et al. A public-private partnership develops and externally validates a 30-day hospital readmission risk prediction model. Online J Public Health Inform. 2013;5:1–17.

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Abbreviations Used

CDS = clinical decision support
EHR = electronic health record