Chapter 1
Healthcare, Data Analytics, and Business Intelligence

Abstract This chapter introduces the healthcare environment and the need for data analytics and business intelligence in healthcare. It overviews the difference between data and information and how both play a major role in decision-making using a set of analytical tools that can be either descriptive and describe events that have happened in the past, diagnostic and provide a diagnosis, predictive and predict events, or prescriptive and prescribe a course of action.

The chapter then details the components of healthcare analytics and how they are used for decision-making improvement using metrics, indicators and dashboards to guide improvement in the quality of care and performance. Business intelligence technology and architecture are then explained with an overview of examples of BI applications in healthcare. The chapter ends with an outline of some software tools that can be used for BI in healthcare, a conclusion, and a list of references.

Keywords Analytics · Business Intelligence (BI) · Data · Information · Healthcare analytics · Metrics · Indicators · BI technology · BI applications

Objectives

By the end of this chapter, you will learn

1. To describe analytics and their use in healthcare
2. To enumerate the different types of analytics
3. To appreciate BI use in healthcare
4. To detail the BI architecture
5. To clearly explain BI and analytics implications in healthcare
6. To give examples of BI applications in healthcare
7. To describe several software tools used for BI

C. El Morr, H. Ali-Hassan, *Analytics in Healthcare*, SpringerBriefs in Health Care Management and Economics, https://doi.org/10.1007/978-3-030-04506-7_1

1.1 Introduction

Today, organizations have access to large amounts of data, whether internal, such as patient/customer detailed profiles and history (medical or purchasing), or external, such as demographics and population data. These data, which are rapidly generated in a very large volume and in different formats, are referred to as big data. In the healthcare field, professionals today have access to vast amounts of data in the form of staff records, electronic patient records, clinical findings, diagnoses, prescription drugs, medical imaging procedures, mobile health, available resources, etc. Managing the data and analyzing it to properly understand it and using it to make well-informed decisions is a challenge for managers and healthcare professionals. Moreover, data analytics tools, also referred to as business analytics or intelligence tools, by large companies such as IBM and SAP and smaller companies such as Tableau and Qlik, are becoming more powerful, more affordable, and easier to use. A new generation of applications, sometimes referred to as end-user analytics or self-serve analytics, are specifically designed for nontechnical users such as business managers and healthcare professionals. The ability to use these increasingly accessible tools with abundant data requires a basic understanding of the core concepts of data, analytics, and interpretation of outcomes that are presented in this book.

What do we mean by analytics? Analytics is the science of analysis—to use data for decision-making [1]. Analytics involves the use of data, analysis, and modeling to arrive at a solution to a problem or to identify new opportunities. Data analytics can answer questions such as (1) what has happened in the past and why, referred to as descriptive analytics; (2) what could happen in the future and with what certainty, referred to as predictive analytics, and (3) what actions can be taken now to control events in the future, referred to as prescriptive analytics [2, 3]. In the healthcare field, analytics can answer questions such as, is there a cancer present in this X-ray image? Or how many nurses do we need during the upcoming holiday season given the patient admission pattern we had last year and the number of patients with flu that we admitted last month? Or how can we optimize the emergency department processes to reduce wait times?

Data analytics have traditionally fallen under the umbrella of a larger concept, called business intelligence, or BI. BI is a conceptual framework for decision support that combines a system architecture, databases and data warehouses, analytical tools, and applications [1]. BI is a mature concept that applies to many fields, including healthcare, despite the presence of the word "business." While remaining a very common term, BI is slowly being replaced by the term analytics, sometimes referring to the same thing. The commonality and differences between BI and analytics will be clarified later in this chapter.

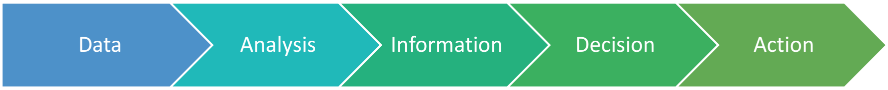


Fig. 1.1 Data to action value chain

1.2 Data and Information

Data are the raw material used to build information; data is simply a collection of facts. Once data are processed, organized, analyzed, and presented in a way that assists in understanding reality and ultimately making a decision, it is called information. Information is ultimately used to make a decision and take a course of action (Fig. 1.1).

1.3 Decision-Making in Healthcare

From an analytics perspective, one can look at healthcare as a domain for decision-making. A nurse or a doctor collects data about a patient (e.g., temperature, blood pressure), reviews an echocardiogram (ECG) screen, and then assesses the situation (i.e., processes the data) and makes a decision on the next step to move the patient forward towards healing. A director of a medical unit in a hospital collects data about the number of inpatients, the number of beds available, the previous year's occupancy in the unit, and the expected flu trends for the season to predict the staffing needs for the Christmas season and make certain decisions about staffing (e.g., vacations, hiring). A radiologist accesses a digital image (e.g., X-ray, ultrasound, computed tomography (CT), magnetic resonance imaging (MRI)), uses the digital image processing tools available on her/his diagnostic workstation to make a diagnosis and reports the presence or absence of a disease. A committee might access admission data, operating room (OR) data, intensive care unit (ICU) data, financial data, or human resource data and use software to prescribe a reorganization of schedules to optimize ED [4, 5], OR [6, 7], and ICU scheduling [8–10].

These are different types of decision-making tasks that require different kinds of analytics that we will explore in detail in Chap. 2. As mentioned above, some of these analytics tools explained above are descriptive of a situation presenting output such as charts and numbers to decision makers, such as the case of the ECG output and the temperature presented to the nurse/doctor. Some other analytics are diagnostic; they present the decision maker with the information necessary to make a diagnosis, such as the case of the software tools used by the radiologist. Some are predictive and assist in making a prediction about the future, such as the case of a software tool used by the director of the medical unit. Finally, other analytics are prescriptive and assist in prescribing a course of action to attain a goal, such as the example of the ED, OR, and ICU scheduling optimization.

1.4 Components of Healthcare Analytics

Data analytics are the systematic access, organization, transformation, extraction, interpretation, and visualization of data using computational power to assist in decision-making. The data are not necessarily voluminous (i.e., big data); there are specific methods for analyzing big data called big data analytics, which are briefly covered in the last chapter of this book.

Trevor Strome's five basic layers of analytics [11] include the following (Fig. 1.2).

1. Business context
2. Data
3. Analytics
4. Quality and performance management
5. Presentation

On the basis of this stack is the business context in which people must define their objectives (including strategic objectives) and measurable goals. In patient-centered care, the voice of the patient is paramount. Once the business context is set and clear, the data context must be defined including the source and quality of the data, its integration, the data management processes, and the infrastructure present or needed to store and manage the data.

The type of analytics is then defined including the tools (e.g., software), the techniques (i.e., algorithms), the stakeholders, the team involved, the data requirements for analysis, the management, and the deployment strategies. The next level consists of defining methods to measure performance and quality, including the processes involved, measurement indicators, achievable targets, and strategies for evaluation and improvement. Finally, the analytics findings are presented in an easy-to-use

Presentation		
Visualization	Dashboards	Reports
Alerts	Mobile	Geospatial
Quality and Performance Management		
Processes	Indicators	Targets
Improvement strategy	Evaluation strategy	
Analytics		
Tools	Techniques	Team
Stakeholders	Requirements	
Deployment	Management	
Data		
Quality	Management	Integration
Infrastructure	Storage	
Business Context		
Objectives	Goals	Patient Voice

Fig. 1.2 Components of healthcare analytics (adapted from Strome [11])

manner to stakeholders/users; hence, visualization options should be explored, including simple reports, graphics-rich dashboards, alerts, geospatial representations, and mobile responsiveness.

1.5 Measurement, Metrics, and Indicators

The amount of data available in hospitals and healthcare organizations is immense. To improve quality and performance, healthcare managers need to make sense of the data available. The objectives are laid out into measurable goals.

For this purpose, managers must set **metrics** [12–16] and **indicators** [17–19]. Metrics are quantitative measurements to measure an aspect of quality or performance in healthcare [11] on a specific scale; on a personal level, blood pressure is a metric that can be used by an individual to measure some aspects of cardiovascular performance/quality. On a system level, hospitals may build many types of metrics to measure their performance and quality of care, for example, the hospital readmission rate within 30 days of discharge, the emergency department wait time, bed occupancy, the length of stay in the hospital, and the number of adverse drug events. An indicator allows managers to detect the state of the current performance and how far it is from a set target.

However, metrics alone are not sufficient; we need to tie a metric to a target goal to determine whether a certain desirable goal has been attained. Metrics that are tied to a certain target (e.g., a certain number target or a range) are called **indicators;** indicators are markers for progress or achievement [20]. Hence, the quality of care and performance of a hospital can be measured by an indicator such as a readmission rate target lower than 7%. If this is justifiable, then any readmission rate above 7% is an indicator of poor quality of care.

Indicators can be consolidated on a screen using different kinds of visualization tools such as figures, charts, colors, or numbers. These indicators displayed in a simple to use and easy to understand way is called a **dashboard**; dashboards display a snapshot of the "health" of an organization (e.g., a hospital). A gradual color scheme is then used to convey the different states of an indicator; for example, a red color usually indicates an "unhealthy" situation (readmission rates considerably above the target), an orange color indicates a situation above the target but not alarming, and a green color indicates situation within the target [21–23]. Examples of dashboards can be seen in Figs. 1.3, 1.4, 1.5, and 1.6.

1.6 BI Technology and Architecture

Laura Madsen defines BI as "the integration of data from disparate source systems to optimize business usage and understanding through a user-friendly interface." [25]. BI is an umbrella term that combines architectures, tools, methodologies,

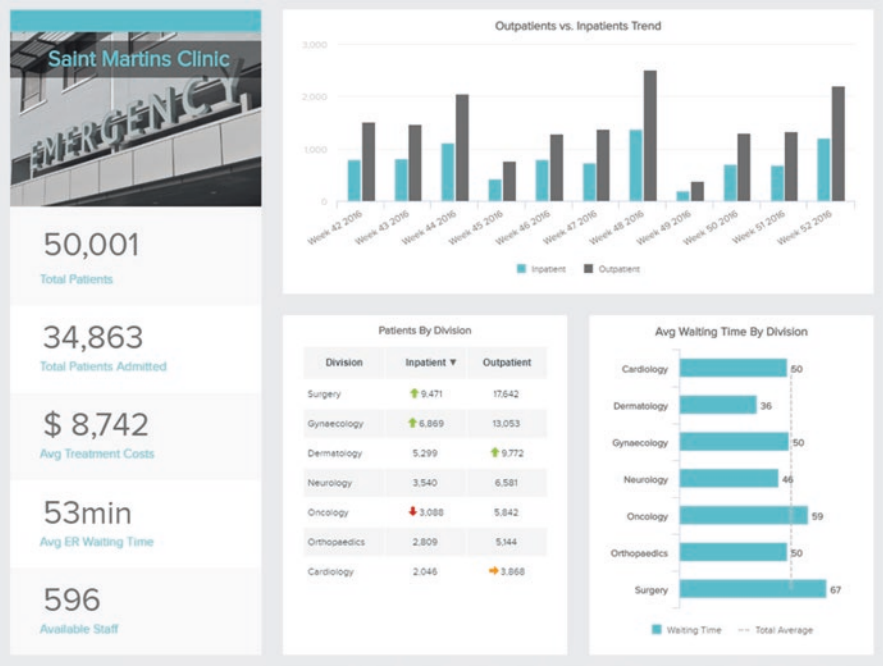


Fig. 1.3 KPI dashboard (Source: datapine.com [24])

Fig. 1.4 Hospital dashboard (Source: datapine.com [24])

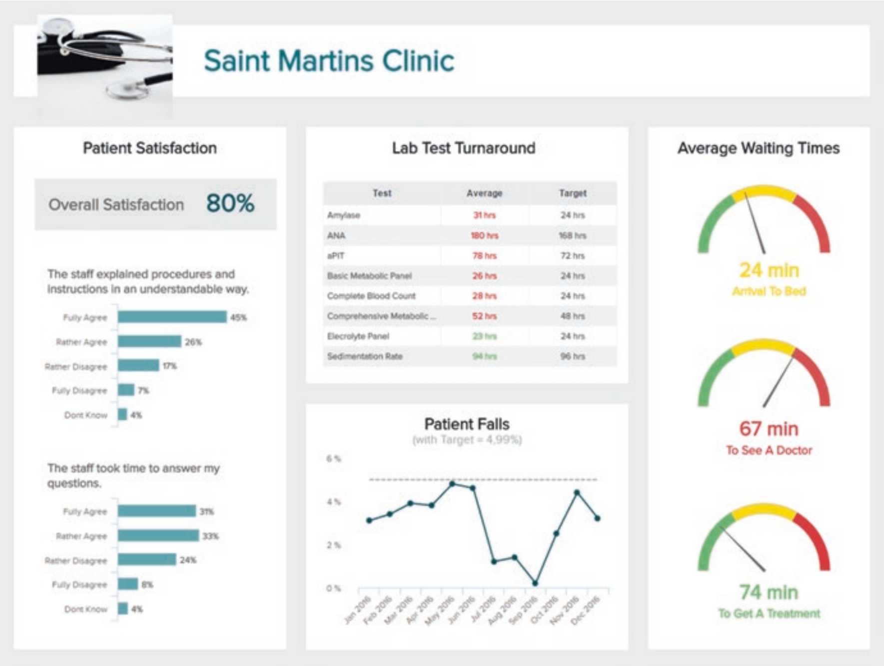


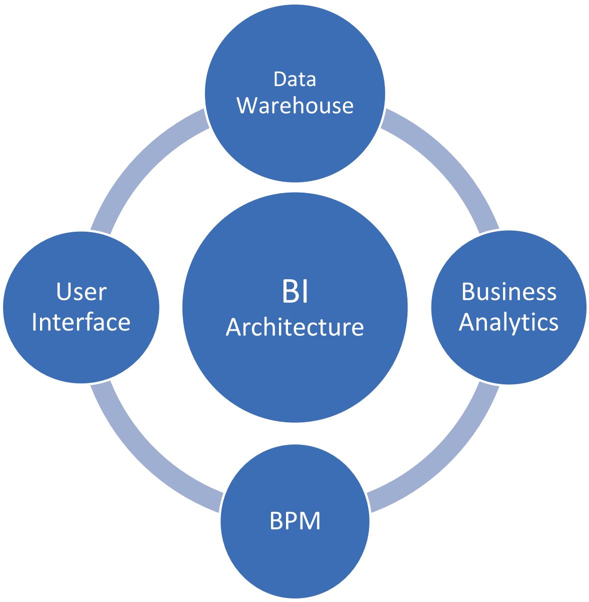
Fig. 1.5 Patient satisfaction dashboard (Source: datapine.com [24])

databases and data warehouses, analytical tools, and applications. The major objective of BI is to enable interactive access to data (and models), to enable manipulation of data and to provide managers, analysts, and professionals with the ability to conduct the appropriate analysis for their needs. BI analyzes historical and current data and transforms it into information and valuable insights (and knowledge), which lead to more informed and better decisions [3]. BI has been very valuable in applications such as customer segmentation in marketing, fraud detection in finance, demand forecasting in manufacturing, and risk factor identification and disease prevention and control in healthcare.

The architecture of BI has four major components: a data warehouse, business analytics, business performance management (BPM), and a user interface. A data warehouse is a type of database that holds source data such as the medical records of patients. It is the cornerstone of medium-to-large BI systems. The data which can be either current or historical are of interest to decision makers and are summarized and structured in a form suitable for analytical activities such as data mining and querying. The second key component is data analytics, which are collections of tools, techniques, and processes for manipulating, mining, and analyzing data stored in the data warehouses. The third key component is business performance management (BPM), which encompasses the tools (business processes, methodologies, metrics, and technologies) used for monitoring, measuring, analyzing, and managing business performance. Finally, BI architecture includes a user interface that

Fig. 1.6 Hospital performance dashboard (Source: datapine.com [24])

Fig. 1.7 Business intelligence architecture's four key components



allows bidirectional communication between the system and its user in the form of dashboards, reports, charts, or online forms. It provides a comprehensive graphical view of corporate performance measures, trends, and exceptions [1]. In this book, we will further explore the concepts of data warehouses (Chap. 2), analytics (Chaps. 3 and 4), and user interfaces (Chap. 5) (Fig. 1.7).

1.7 BI Applications in Healthcare

Health organizations need to take actions to be able to measure, monitor, and report on the quality, effectiveness, and value of care. Madsen states that healthcare BI can be defined as "the integration of data from clinical systems, financial systems, and other disparate data sources into a data warehouse that requires a set of validated data to address the concepts of clinical quality, effectiveness of care, and value for business usage" [26]. Data quality, leadership, technology and architecture, and value and culture represent the five facets of healthcare BI (Fig. 1.8).

Examples of BI in healthcare include clinical and business intelligence systems, such as the one implemented at the Broward Regional Health Planning Council in Florida [27], which was built on a regional level to enable healthcare service decision makers, healthcare service planners, and hospitals to access live data generated by many data sources in Florida, including medical facilities utilization data, diagnosis-related group data (DRGs), and health indicator data. The components of such a BI system include extraction, transformation and loading (ETL), a data warehouse, and analytical tools (Fig. 1.9).

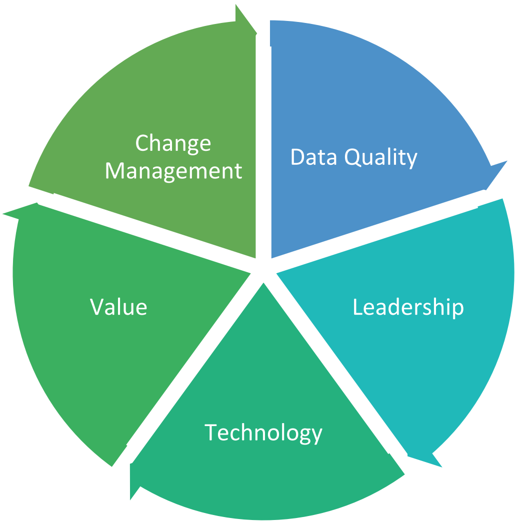


Fig. 1.8 The five facets of healthcare BI (adapted from Laura Madsen's 5 tenets of healthcare BI [26])

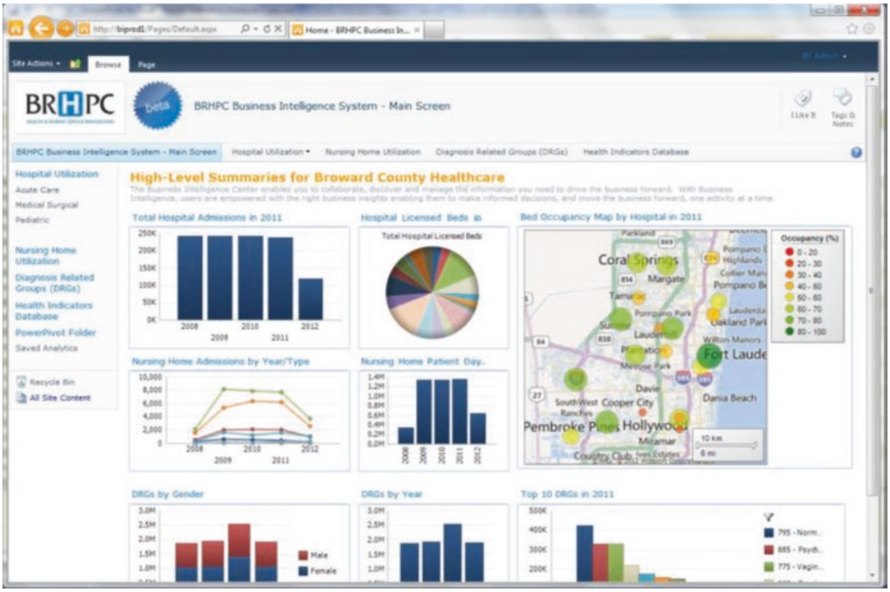


Fig. 1.9 A high-level dashboard of the Broward Regional Health Planning Council business intelligence system (Source: AlHazme et al. [27])

Within radiology, BI can be used to improve quality, safety, efficiency, and cost-effectiveness as well as patient outcomes. The radiology department uses a number of BI metrics [28]; some metrics, such as turnaround time, imaging modality utilization, departmental patient throughput, and wait times, are related to "efficiency"; others relate to quality and safety, such as radiation dose monitoring and reduction and the detection of discrepancies between radiology coding and study reporting [28]. Other BI systems have been proposed to monitor performance by monitoring indicators such as 30-day readmission rates and identifying conditions that most influence readmissions, patients' satisfaction or even monitoring in real-time the medication purchasing and utilization for budgetary/cost purposes [29].

1.8 BI and Analytics Software Providers

The BI and analytics applications landscape is covered by a large number of software vendors. Some of the application providers are software giants such as Microsoft, IBM, SAP, and Oracle, others are large contributors in the field of statistics such as SAS, and some are smaller and specialized providers such as Tableau and Qlik. Every year, Gartner, a consultancy firm, publishes its Magic Quadrant for Analytics and Business Intelligence Platforms (https://www.gartner.com/doc/3861464/magic-quadrant-analytics-business-intelligence). Each year, Gartner places the 20 top vendors in the quadrant based on the completeness of their vision and ability to execute (Fig. 1.10). The companies that score high on both dimensions

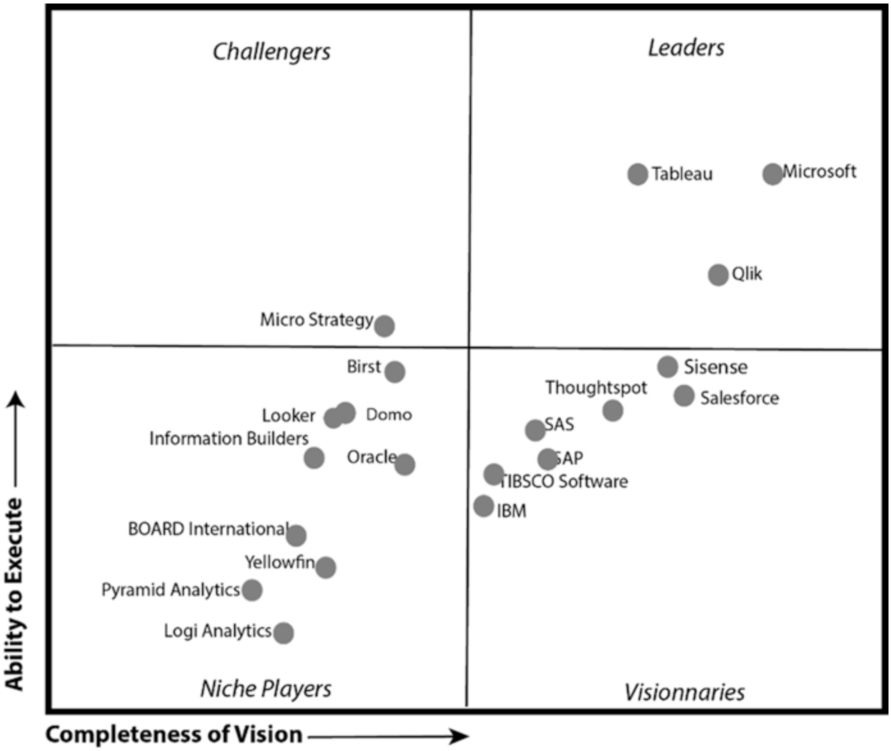


Fig. 1.10 Magic quadrant for analytics and BI platforms (adapted from Gartner Magic quadrant [30])

are labeled as Leaders, and those who score lower are labeled Niche Players. Visionaries are those who score high on completeness but low on the ability to execute while the last quadrant is for Challengers.

In the February 2018 report, three companies led the pack for the third year in a row: Microsoft, Tableau, and Qlik. The next group of vendors that have remained in the quadrant in the past 3 years, moving between Leaders and Visionaries, are SAS, SAP, IBM, and Tibco [31]. The companies listed above are general solution providers for many industries, including healthcare. A recent list of top healthcare business intelligence companies by hospital users was led by Epic Systems, MEDHOST, and Siemens but also included SAS and Qlik [32]. In the Software Toolbox sections of this book, we will focus on providers that are either leaders in the field of analytics or specialize in healthcare analytics.

To obtain a sense of what analytics is and what outcomes it can generate, we suggest you test the different demonstrations provided by Qlik at https://demos.qlik.com/. You can select either of their two products, Qlik Sense or QlikView. The former is focused on the user interface and dashboards, while the latter focuses on analytics. In both cases, you can select the healthcare industry to experience applications such as visualizing operating room management, efficiency and utilization, or analysis of hospital readmissions.

1.9 Conclusion

Paired with abundant data, advanced technology, and easier use, business intelligence (BI) and analytics have recently gained great popularity due to their ability to enhance performance in any industry or field. Analytics, considered by many as part of BI, extracts, manipulates and analyzes data, transforming it into information that helps professionals make well-informed decisions. It supports taking action and generating knowledge. In the healthcare field, analytics plays a major role in areas such as diagnosis, admissions, and prevention. In this chapter, we explored the basic facets of BI with its key components, such as data warehouses and analytical capabilities. Analytics with its four categories, descriptive, diagnostic, predictive, and prescriptive analytics, will be explored in more detail in the next chapter.

References

1. R. Sharda, D. Delen, E. Turban, J. Aronson, and T. P. Liang, *Businesss Intelligence and Analytics: Systems for Decision Support*. 2014.
2. N. Kalé and N. Jones, *Practical Analytics*. Epistemy Press, 2015.
3. R. Sharda, D. Delen, and E. Turban, *Business Intelligence: A Managerial Perspective on Analytics: A Managerial Perspective on Analytics*. Pearson, 2015, pp. 416–416.
4. J. Akin, J. A. Johnson, J. P. Seale, and G. P. Kuperminc, "Using process indicators to optimize service completion of an ED drug and alcohol brief intervention program," (in eng), *Am J Emerg Med,* vol. 33, no. 1, pp. 37–42, Jan 2015.
5. D. Steward, T. F. Glass, and Y. B. Ferrand, "Simulation-Based Design of ED Operations with Care Streams to Optimize Care Delivery and Reduce Length of Stay in the Emergency Department," (in eng), *J Med Syst,* vol. 41, no. 10, p. 162, Sept 6 2017.
6. M. D. Basson, T. W. Butler, and H. Verma, "Predicting patient nonappearance for surgery as a scheduling strategy to optimize operating room utilization in a veterans' administration hospital," (in eng), *Anesthesiology,* vol. 104, no. 4, pp. 826–34, Apr 2006.
7. C. J. Warner *et al.*, "Lean principles optimize on-time vascular surgery operating room starts and decrease resident work hours," (in eng), *J Vasc Surg,* vol. 58, no. 5, pp. 1417–22, Nov 2013.
8. R. Aslakson and P. Spronk, "Tasking the tailor to cut the coat: How to optimize individualized ICU-based palliative care?," (in eng), *Intensive Care Med,* vol. 42, no. 1, pp. 119–21, Jan 2016.
9. J. Kesecioglu, M. M. Schneider, A. W. van der Kooi, and J. Bion, "Structure and function: planning a new ICU to optimize patient care," (in eng), *Curr Opin Crit Care,* vol. 18, no. 6, pp. 688–92, Dec 2012.
10. W. J. Schellekens *et al.*, "Strategies to optimize respiratory muscle function in ICU patients," (in eng), *Crit Care,* vol. 20, no. 1, p. 103, Apr 19 2016.
11. T. L. Strome, *Healthcare analytics for quality and performance improvement*. Hoboken, NJ: Wiley, 2013.
12. C. Daluwatte, J. Vicente, L. Galeotti, L. Johannesen, D. G. Strauss, and C. G. Scully, "A novel ECG detector performance metric and its relationship with missing and false heart rate limit alarms," (in eng), *J Electrocardiol,* vol. 51, no. 1, pp. 68–73, Jan - Feb 2018.
13. K. Honeyford, P. Aylin, and A. Bottle, "Should Emergency Department Attendances be Used With or Instead of Readmission Rates as a Performance Metric?: Comparison of Statistical Properties Using National Data," (in eng), *Med Care,* Mar 29 2018.

14. D. A. Maldonado, A. Roychoudhury, and D. J. Lederer, “A novel patient-centered "intention-to-treat" metric of U.S. lung transplant center performance,” (in eng), *Am J Transplant,* vol. 18, no. 1, pp. 226–231, Jan 2018.
15. J. D. Markley, A. L. Pakyz, R. T. Sabo, G. Bearman, S. F. Hohmann, and M. P. Stevens, “Performance of a Novel Antipseudomonal Antibiotic Consumption Metric Among Academic Medical Centers in the United States,” (in eng), *Infect Control Hosp Epidemiol,* vol. 39, no. 2, pp. 229–232, Feb 2018.
16. S. Stevanovic and B. Pervan, “A GPS Phase-Locked Loop Performance Metric Based on the Phase Discriminator Output,” (in eng), *Sensors (Basel),* vol. 18, no. 1, Jan 19 2018.
17. P. Kaushik, “Physician Burnout: A Leading Indicator of Health Performance and "Head-Down" Mentality in Medical Education-I,” (in eng), *Mayo Clin Proc,* vol. 93, no. 4, p. 544, Apr 2018.
18. K. D. Olson, “In Reply-Physician Burnout: A Leading Indicator of Health Performance and "Head-Down" Mentality in Medical Education-I and II,” (in eng), *Mayo Clin Proc,* vol. 93, no. 4, pp. 545–547, Apr 2018.
19. J. Peck and O. Viswanath, “Physician Burnout: A Leading Indicator of Health Performance and “Head-Down” Mentality in Medical Education-II,” (in eng), *Mayo Clin Proc,* vol. 93, no. 4, pp. 544–545, Apr 2018.
20. Center for Disease Control. (2018, April 22). *Developing Evaluation Indicators*. Available: https://www.cdc.gov/std/Program/pupestd/Developing%20Evaluation%20Indicators.pdf
21. Z. Azadmanjir, M. Torabi, R. Safdari, M. Bayat, and F. Golmahi, “A Map for Clinical Laboratories Management Indicators in the Intelligent Dashboard,” (in eng), *Acta Inform Med,* vol. 23, no. 4, pp. 210–4, Aug 2015.
22. M. C. Schall, Jr., L. Cullen, P. Pennathur, H. Chen, K. Burrell, and G. Matthews, “Usability Evaluation and Implementation of a Health Information Technology Dashboard of Evidence-Based Quality Indicators,” (in eng), *Comput Inform Nurs,* vol. 35, no. 6, pp. 281–288, Jun 2017.
23. P. Stattin *et al.*, “Dashboard report on performance on select quality indicators to cancer care providers,” (in eng), *Scand J Urol,* vol. 50, no. 1, pp. 21–8, 2016.
24. Datapine.com. (2018, September 17). *Healthcare Dashboards Examples*. Available: https://www.datapine.com/dashboard-examples-and-templates/healthcare#patient-satisfaction-dashboard
25. L. Madsen, “Business Intelligence An Introduction,” in *Healthcare Business Intelligence: A Guide to Empowering Successful Data Reporting and Analytics*: Wiley, 2012.
26. L. Madsen, “The Tenets of Healthcare BI,” in *Healthcare Business Intelligence: A Guide to Empowering Successful Data Reporting and Analytics*: Wiley, 2012.
27. R. H. AlHazme, A. M. Rana, and M. De Lucca, “Development and implementation of a clinical and business intelligence system for the Florida health data warehouse,” (in eng), *Online J Public Health Inform,* vol. 6, no. 2, p. e182, 2014.
28. T. S. Cook and P. Nagy, “Business intelligence for the radiologist: making your data work for you,” (in eng), *J Am Coll Radiol,* vol. 11, no. 12 Pt B, pp. 1238–40, Dec 2014.
29. B. Pinto and B. I. Fox, “Clinical and Business Intelligence: Why It’s Important to Your Pharmacy,” (in eng), *Hosp Pharm,* vol. 51, no. 7, p. 604, Jul 2016.
30. C. Howson, R. L. Sallam, J. L. Richardson, J. Tapadinhas, C. J. Doine, and A. Woodward, “Magic Quadrant for Analytics and Business Intelligence Platforms,” Gartner Group February 26, 2018. Available: https://b2bsalescafe.files.wordpress.com/2018/03/magic-quadrant-for-analytics-and-business-intelligence-platforms.pdf.
31. B. Aziza. (2018) Gartner Magic Quadrant: Who’s Winning In The Data And Machine Learning Space. *Forbes*. Available: https://www.forbes.com/sites/ciocentral/2018/02/28/gartner-magic-quadrant-whos-winning-in-the-data-machine-learning-space/#7dca83b37dab
32. K. Monica, “Top Healthcare Business Intelligence Companies by Hospital Users,” ed, 2017.