PERSPECTIVE

Modern Analytics and the Future of Quality and Performance Excellence

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Analytics is the use of data, information technology, statistical analysis, quantitative methods, and mathematical or computer-based models to help managers gain improved insight about their business operations and make better, fact-based decisions. While the disciplines underlying analytics—statistics, business intelligence, and operations research/management science—have been around for well over a half-century, the integration of these disciplines, supported by various tools, has led to new and more powerful ways to view, understand, and use data and information intelligently. Despite the extensive interest in analytics within business, very little has been published about it in ASQ publications such as Quality Progress *and* Quality Management Journal. *The importance of modern analytics is becoming recognized in the Baldrige Criteria and represents a significant opportunity for executives who pursue performance excellence, quality managers, and academic researchers.*

INTRODUCTION

In 2007, Thomas H. Davenport and Jeanne G. Harris wrote a groundbreaking book, *Competing on Analytics: The New Science of Winning* (Davenport and Harris 2007). They described how many organizations are using analytics strategically to make better decisions and improve customer and shareholder value. An early definition of analytics is "a process of transforming data into actions through analysis and insights in the context of organizational decision making and problem solving" (Liberatore and Luo 2010). Another is "the use of data, information technology, statistical analysis, quantitative methods, and mathematical or computer-based models to help managers gain improved insight about their business operations and make better, fact-based decisions" (Evans 2016).

Over the last decade, applications of analytics have grown exponentially in business, healthcare, and other industries (Davenport 2013; McNeill 2013). A survey by the American Management Association (AMA) of approximately 800 business executives in more than 50 industries and 40 countries noted that "Overall, 58 percent of participants report that analytics are already vital to their organization, and that rises to 82 percent when asked about five years from now" (AMA 2013). Figure 1 shows the remarkable growth of jobs in business analytics.

Analytics is changing how organizations manage. Tools and techniques of modern analytics are used across many areas in a wide variety of organizations to improve the management of customer relationships, financial and marketing activities, human capital, supply chains,

Figure 1 Business analytics job trends

Source: Indeed.com

and many other areas. Leading banks use analytics to predict and prevent credit fraud. Manufacturers use analytics for production planning, purchasing, and inventory management. Retailers use analytics to recommend products to customers and optimize marketing promotions. Pharmaceutical firms use it to get life-saving drugs to market more quickly. Even sports teams are using business analytics to determine both game strategy and optimal ticket prices (Davis 2010).

Research has also suggested that organizations are overwhelmed by data and struggle to understand how to use data to achieve business results, and that most organizations simply don't understand how to use analytics to improve their businesses. Thus, understanding the capabilities and techniques of analytics is vital to managing in today's business environment. The importance of modern analytics is becoming recognized in the Baldrige Criteria and represents a significant opportunity for executives who pursue performance excellence, quality managers, and academic researchers.

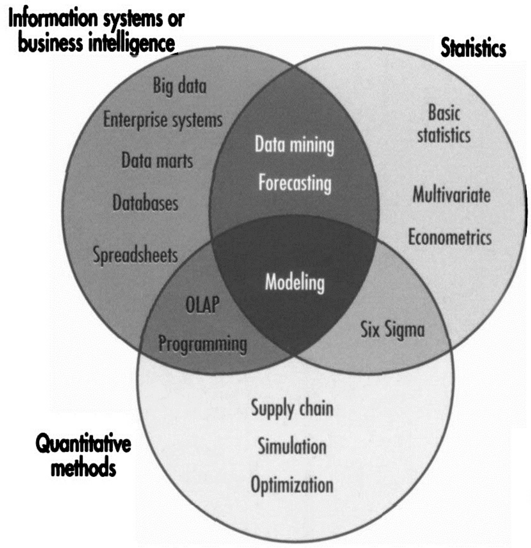
Quality professionals need analytics skills for several reasons. First, everyone is doing it. The business case for analytics is compelling, and the profession must maintain a state of the art. Second, analytics adds value beyond Six Sigma; it provides powerful tools that both complement and transcend Six Sigma. Analytics can provide new insights that conventional tools cannot. Third, analytics—particularly new approaches to data visualization—facilitates communication. Quality professionals must continue to develop their communication skills to interact effectively with both functional managers and analytics professionals in modern organizations.

ORIGINS OF BUSINESS ANALYTICS

Analytical methods, in one form or another, have been used in business for more than a century. However, the modern evolution of analytics began with the introduction of computers in the late 1940s and their development through the 1960s and beyond. Early computers provided the ability to store and analyze data in ways that were either very difficult or impossible to do so manually. This facilitated the collection, management, analysis, and reporting of data, which is often called business intelligence (BI), a term that was coined in 1958 by an IBM researcher, Hans Peter Luhn (Luhn 1958). Statistics also has a long and rich history, yet only recently has it been recognized as an important element of business, driven to a large extent by the massive growth of data available today. Statistical methods include the basic tools of description, exploration, estimation, and inference, as well as more advanced techniques like regression, forecasting, and data mining. Statistical methods allow one to gain a richer understanding of data that goes beyond business intelligence reporting by not only summarizing data succinctly but also finding unknown and interesting relationships among the data. Google's chief economist stated that statisticians surely have the "really sexy job" for the next decade (Swain 2013).

Much of modern analytics stems from the analysis and solution of complex decision problems using mathematical or computer-based models—a discipline known as operations research (OR), or management science (MS). Many OR/MS applications use modeling and optimization—techniques for translating real problems into mathematics, spreadsheets, or other computer languages, and using them to find the best solutions and decisions. Decision support systems (DSS) began to evolve in the 1960s by combining business intelligence concepts with OR/MS models to create analytical-based computer systems to support decision making.

Figure 2 A business analytics framework



Source: Klimberg and Miori 2010

THE SCOPE OF MODERN ANALYTICS

Modern analytics can be viewed as an integration of the three fundamental disciplines: business intelligence/information systems (BI/IS), statistics, and quantitative methods/operations research (see Figure 2). These disciplines have been around for more than half a century. However, their integration, supported by various tools such as spreadsheets, statistical software, and more complex business intelligence suites that integrate data with analytical software, have led to new and more powerful ways to view, understand, and use data and information intelligently. For example, data mining can be characterized as the integration of BI/IS and statistics. Spreadsheets and formal models allow one to manipulate data to perform what-if analysis—how specific combinations of inputs that reflect key assumptions will affect model outputs. What-if analysis results from integrating concepts of BI/IS with operations research.

Perhaps the most useful component of business analytics, which makes it truly unique, is visualization, which is an essential component of each of these three areas, and often integrates all three of them. Visualizing data, model results, and analyses can reveal surprising patterns and relationships and provide a way of easily communicating data at all levels of an organization.

Modern analytics is often characterized from three perspectives (Lustig et al. 2010):

1. *Descriptive analytics.* The use of data to understand past and current performance and make informed decisions. Descriptive analytics summarizes data into meaningful charts and reports, for example, about budgets, sales, revenues, or cost. This process allows managers to obtain standard and customized reports and then drill down into the data and make queries to understand the impact of an advertising campaign, for example, review performance to find problems or areas of opportunity, and identify patterns and trends in data.
2. *Predictive analytics.* Analyzing past performance in an effort to predict the future by examining historical data, detecting patterns or relationships in these data, and then extrapolating these relationships forward in time. Using advanced techniques, predictive analytics can help to detect hidden

patterns in large quantities of data to segment and group data into coherent sets in order to predict behavior and detect trends.

3. *Prescriptive analytics.* Using optimization to identify the best alternatives to minimize or maximize some objective. The mathematical and statistical techniques of predictive analytics can also be combined with optimization to make decisions that take into account the uncertainty in the data.

Modern analytics is often associated with "big data." Analytics professionals have coined this term to refer to massive amounts of business data from a wide variety of sources, much of which is available in real time, and much of which is uncertain or unpredictable. IBM calls these characteristics volume, variety, and velocity. Most often, big data revolve around customer behavior and customer experiences. Big data provide an opportunity for organizations to gain a competitive advantage—if the data can be understood and analyzed effectively to make better decisions

Big data come from many sources, and can be numerical, textual, and even audio and video data. Big data are captured using sensors (for example, supermarket scanners or industrial sensors), click streams from the Web, customer transactions, emails, tweets and social media, and other ways. Big data sets are unstructured and messy, requiring sophisticated analytics to integrate and process the data, and understand the information contained in them. Not only are big data being captured in real time, but they must be incorporated into business decisions at a faster rate. Processes such as fraud detection must be analyzed quickly to have value. IBM has added a fourth dimension: veracity—the level of reliability associated with the data.

ANALYTICS IN BALDRIGE AND STRATEGIC MANAGEMENT

IBM suggests that traditional management approaches are evolving in today's analytics-driven environment to include more fact-based decisions as opposed to judgment and intuition, more prediction rather than reactive decisions, and the use of analytics by everyone at the point where decisions are made rather than relying on skilled experts in a consulting group (IBM 2009). These principles have been reflected in the Baldrige Criteria for many years. The *2015-2016 Baldrige Excellence Framework* (Baldrige Performance Excellence Program 2015) notes the importance of data and analytics in the Core Value of Management by Fact, and in its glossary definition of analysis:

> *Management by fact requires you to measure and analyze your organization's performance, both inside the organization and in your competitive environment. Measurements should derive from business needs and strategy, and they should provide critical data and information about key processes, outputs, results, outcomes, and competitor and industry performance. Organizations need many types of data and information to effectively manage their performance.*
>
> *Analysis means extracting larger meaning from data and information to support evaluation, decision making, improvement, and innovation. It entails using data to determine trends, projections, and cause-and-effect relationships that might not otherwise be evident.*

Various research studies have discovered strong relationships between a company's performance in terms of profitability, revenue, and shareholder return and its use of analytics. Thus, one would surmise that analytics is an essential component of higher-scoring Baldrige applicants, and this supports the new role of analytics and big data in the 2015-2016 Baldrige Criteria:

> *For all organizations, turning data into knowledge and knowledge into useful strategic insights is the real challenge of big data. While the volume of data an organization must assimilate and use in decision making may vary widely, all organizations are faced with using data from different sources and of varying quality.*

Various elements of the Baldrige Criteria explicitly address both descriptive and predictive analytics implicitly:

- *Strategy considerations. How do you collect and analyze relevant data and develop information for your strategic planning process?*

- *Performance projections. For these key performance measures or indicators, what are your performance projections for your short- and longer-term planning horizons? How does your projected performance on these measures or indicators compare with your projections of the performance of your competitors or comparable organizations and with key benchmarks, as appropriate?*
- *Performance measures. How do you use data and information to track daily operations and overall organizational performance?*
- *Future performance. How do you project your organization's future performance?*

This discussion suggests that practitioners who use Baldrige need to fully understand the basic tools of modern analytics and be able to apply them effectively in their organizations.

ANALYTICS AND THE QUALITY PROFESSION

Despite the extensive amount of activity surrounding analytics in business and academia, the quality profession appears to be lagging behind analytic trends. Only a few articles in *Quality Progress* have addressed some of the concepts of modern analytics. "Real-time data acquisition is becoming the norm. These developments are having and will continue to have major effects on how quality professionals and statisticians conduct product and process design and quality improvement projects (Snee, DeVeau, and Hoerl 2014)." Liu (2015) observes that "Handling big data is not easy." A study found more than 70 percent of executives think they are incapable of leveraging what data are saying, and more than 50 percent of organizations do not know how to make business decisions based on predictive analytics. However, he cites only traditional tools such as fishbone and affinity diagrams for analysis.

In traditional quality management activities, many opportunities for using descriptive and predictive analytics exist; prescriptive analytics is more limited because it is not specifically data focused, but has applications in process optimization and systems simulation. In this section, the author briefly reviews the roles and applications of traditional analytical tools in quality, as well as the potential of modern analytics approaches.

Statistics also has a long history in quality management, beginning with industrial quality assurance in the Bell System nearly a century ago, and the work of the early pioneers of quality—Walter Shewhart, Harold Dodge, George Edwards, and others such as Joseph Juran and W. Edwards Deming (Jenney and Newton 1969; Bisgaard 2007; Evans and Lindsay 2014). Statistical methods are fundamental to Six Sigma practice. In fact, Six Sigma has led to a renaissance of statistics in business; workers at all organizational levels are receiving statistical training that has never been done before.

Business intelligence tools are often applied in quality. Some of the basic approaches are simple database queries. These are often implemented using spreadsheets, Microsoft Access databases, and supported by predictive models, and scenario and "what-if" analyses. Vera-Baquero and Colomo-Palacios (2013), for example, review the application of statistical and artificial intelligence techniques to measure and analyze process-related data. Quality managers use these techniques routinely. For example, McMahon (2013) discusses the use of real-time analytics in pharmaceutical quality control. The 2007 Baldrige application summary for PRO-TEC explains the use of such methods in daily control:

> *Performance measures and results are compared to performance goals and tracked to ensure that they meet the process requirements. … All measurement devices including load cells, thermocouples, transducers, and others are calibrated on a defined schedule. Statistical techniques including control charts, capability studies, and pivot tables are then used on the collected data to ensure performance guarantees and quick response to reduce process variability. Statistical practices are used to drive process control in addition to process enhancements and improvements. Customers receive certified test results of product properties after material is shipped. Material suppliers also provide PRO-TEC with certificates of compliance to ensure and*

> *provide proof that their material meets all of the necessary performance and quality requirements. Day-to-day opportunities use in-process measures to ensure the processes meet process requirements.* (PRO-TEC 2007)

> *The QA department, in addition to tracking standard quality assurance measures for steel, also supports innovation by analyzing what process conditions support optimal conditions and minimal variation for product quality. The IS department looks at process data and does statistical analysis in support of updating process models and tables. The results of these analyses are used to drive departmental and organizational decision making.* (PRO-TEC 2007)

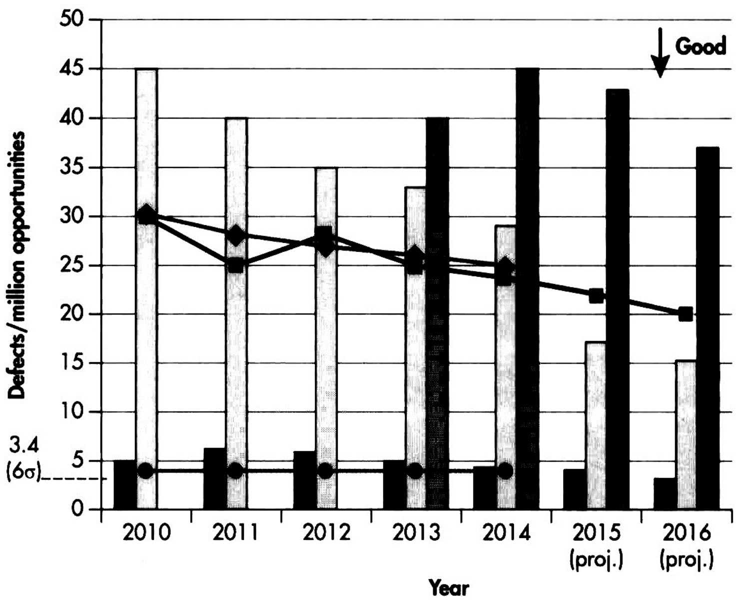
Data visualization represents one of the most effective tools for communicating analytic information. Sun et al. (2013) survey the state-of-the-art of visual analytics and applications by classifying them into categories of space and time, multivariate, text, graph and network, and others. As with other analytic techniques, visualization is not new. For example, Max (1995) discussed the use of visualization techniques to enhance the validation of system quality. Two visualization algorithms for viewing system instrument stabilities are described, which allow a system manager to convincingly document the traceability and stability of the instruments in a large system. Bisgaard and Huang (2008) propose a simple method for visualizing the results of principal components analysis to complement existing graphical methods for multivariate time series data applicable for process analysis and control.

Category 7 of the Baldrige Criteria relies almost exclusively on effective data visualization of performance results. The criteria require demonstration of effective performance levels, positive trends, comparative data, and integration with business strategy. The criteria also provide advice for effective data visualization (see Figure 3, drawn from the criteria).

- Both axes and units of measure are clearly labeled.
- Levels and trends are reported for a key performance measure—defects per million opportunities.
- Results are presented for several years.
- An arrow indicates that a downward trend is good for this measure.
- Appropriate comparisons are shown clearly.
- In a single graph, the organization segments its results for its three product lines, showing that they are tracked separately.
- The organization projects improved performance, including discontinuous or breakthrough improvement in 2015 relative to prior performance for product line B.

Data visualizations are often summarized in "dashboards" and "scorecards" to report key performance measures. A dashboard is a visual representation of a set

Figure 3 Example performance results chart



Source: 2015-16 Baldrige Criteria

of key business measures. It is derived from the analogy of an automobile's control panel, which displays speed, gasoline level, temperature, and so on. The use of dashboards has been reported by many Baldrige recipients.

> *Assessment of communication approaches revealed an opportunity for SMC* [Schneck Medical Center] *leaders to develop a more systematic approach to review and analyze performance at all levels of the organization. In response to this, the organizational dashboard was redesigned and department scorecard indicators were reevaluated and updated to include only measurements that were required, actionable, and meaningful.*

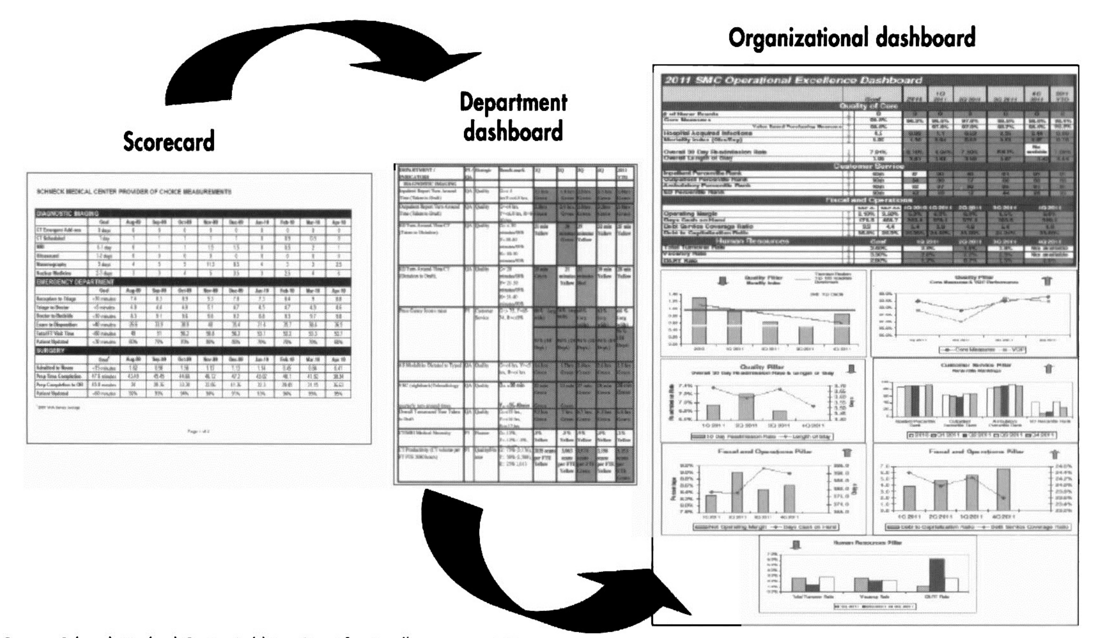
Figure 4 illustrates this process.

Simulation provides useful analytic capabilities in quality. Batson and Williams (1998) note that process simulation has been used for decades to study issues of capacity, throughput, utilization, and other productivity measures, and as simulation technology has become more accessible to nonexperts, applications in quality improvement, quality planning, and business process reengineering have appeared. Process simulation is a useful tool for Six Sigma applications, especially those involving customer service improvement, cycle-time reduction, and variability reduction (Fleming and Manson 2002).

Monte-Carlo simulation randomly selects model inputs and evaluates the outcomes, leading to distributions of potential outcomes of key model variables along with their likelihood of occurrence. This type of simulation provides an assessment of the risk associated with a set of decisions that analytical methods generally cannot capture and is well suited to spreadsheet applications. Monte Carlo simulation is often used in Design for Six Sigma (DFSS) to identify key parameters driving variation, create robust designs, and optimize parameters and tolerances. It is also used in design of experiments for the analysis of tolerances and reliability or to statistically assess the effect of individual tolerances on an assembly or process.

Liu (2015) notes that quality professionals must learn the skills associated with big data—statistics, predictive modeling, and basic computer programming—and learn to work cohesively with big data scientists. One of the most powerful methods of modern analytics is data and text mining (Mariscali, Marban, and Fernandez 2010). Data mining is focused on better understanding characteristics and patterns among

Figure 4 Schneck Medical Center dashboard process



Source: Schneck Medical Center Baldrige Quest for Excellence presentation variables in large databases using a variety of statistical and analytical tools. Many standard statistical tools, as well as more advanced ones, are used extensively in data mining. Data mining can be considered part descriptive and part prescriptive. As a descriptive tool, data mining focuses on identifying patterns in data without manual intervention. The prescriptive nature of data mining is focused on predicting relationships or future values of variables of interest.

Some common approaches in data mining include the following:

- *Data exploration and reduction.* This often involves identifying groups in which the elements of the groups are in some way similar. This approach is often used to understand differences among customers and segment them into homogenous groups.
- *Cluster analysis.* Cluster analysis, also called data segmentation, is a collection of techniques that seeks to group or segment a collection of objects (that is, observations or records) into subsets or clusters, such that those within each cluster are more closely related to one another than objects assigned to different clusters.
- *Classification.* Classification is the process of analyzing data to predict how to classify a new data element. An example of classification is spam filtering in an email client. By examining textual characteristics of a message (subject header, key words, and so on), the message is classified as junk or not.
- *Discriminant analysis.* Discriminant analysis is a technique for classifying a set of observations into predefined classes. The purpose is to determine the class of an observation based on a set of predictor variables. Based on the training data set, the technique constructs a set of linear functions of the predictors, known as discriminant functions, which have the form $L = b_1X_1 + b_2X_2 + \ldots + b_nX_n + c$, where the bs are weights, or discriminant coefficients, the Xs are the input variables, or predictors, and c is a constant or the intercept. These discriminant functions are used to predict the category of a new observation.
- *Logistic regression.* Logistic regression is a variation of ordinary regression in which the dependent variable is categorical. However, whereas multiple linear regression seeks to predict the numerical value of the dependent variable y based on the values of the dependent variables, logistic regression seeks to predict the probability that the output variable will fall into a category based on the values of the independent (predictor) variables.
- *Association.* Association is the process of analyzing databases to identify natural associations among variables and create rules for target marketing or buying recommendations. For example, Netflix uses association to understand what types of movies a customer likes and provide recommendations based on the data.
- *Cause-and-effect modeling.* Cause-and-effect modeling is the process of developing analytic models to describe the relationship between metrics that drive business performance, for instance, profitability, customer satisfaction, or employee satisfaction. Understanding the drivers of performance can lead to better decisions to improve performance. For example, the controls group of Johnson Controls, Inc. examined the relationship between satisfaction and contract-renewal rates. They found that 91 percent of contract renewals came from customers who were either satisfied or very satisfied, and customers who were not satisfied had a much higher defection rate. Their model predicted that a one-percentage-point increase in the overall satisfaction score was worth $13 million in service contract renewals annually. As a result, they identified decisions that would improve customer satisfaction (Hoisington and Naumann 2003).

One important application of data mining in quality and performance excellence is associated with customer engagement (a key element of the Baldrige Criteria). Bijmolt et al. (2010) discuss analytical models for customer engagement, which go beyond models for customer transactions. These models pertain to the subsequent stages of the customer life cycle: customer acquisition, customer development, and customer retention. Important developments regarding data availability allow for more detailed and advanced analysis in each of these stages, which supports management of customer engagement.

Regression and correlation analysis are key tools for cause-and-effect modeling. Prior versions of the Baldrige Criteria (2011-2012 and earlier) provide explicit guidance in potential types of analyses for obtaining business insight:

> *Analyses that your organization conducts to gain an understanding of performance and needed actions may vary widely depending on your type of organization, size, competitive environment, and other factors. Examples of possible analyses include the following:*
>
> - *How product improvements correlate with key customer indicators, such as customer satisfaction, customer loyalty, and market share*
> - *Cost and revenue implications of customer-related problems and effective problem resolution*
> - *Interpretation of market share changes in terms of customer gains and losses and changes in customer engagement*
> - *Improvement trends in key operational performance indicators, such as productivity, cycle time, waste reduction, new product introduction, and defect levels*
> - *Relationships among personal learning, organizational learning, and the value added per employee*
> - *Financial benefits derived from improvements in workforce safety, absenteeism, and turnover*
> - *Benefits and costs associated with education, training, including e-learning and other distance learning opportunities*
> - *Benefits and costs associated with improved organizational knowledge management and sharing*
> - *The relationship between knowledge management and innovation*
> - *How the ability to identify and meet workforce capability and capacity needs correlates with retention, motivation, and productivity*
> - *Cost and revenue implications of workforce-related problems and effective problem resolution*
> - *Individual or aggregate measures of productivity and quality relative to competitors' performance*
> - *Cost trends relative to competitors' trends*
> - *Relationships among product quality, operational performance indicators, and overall financial performance trends as reflected in indicators such as operating costs, revenues, asset utilization, and value added per employee*
> - *Allocation of resources among alternative improvement projects based on cost/benefit implications or environmental and societal impact*
> - *Net earnings or savings derived from quality, operational, and workforce performance improvements*
> - *Comparisons among business units showing how quality and operational performance improvement affect financial performance*
> - *Contributions of improvement activities to cash flow working capital use, and shareholder value*
> - *Profit impacts of customer loyalty*
> - *Cost and revenue implications of new market entry including global market expansion*
> - *Market share versus profits*
> - *Trends in economic, market, and stakeholder indicators of value and the impact of these trends on organizational sustainability*

Other applications in more traditional quality assurance include the work of Da Cunha, Agard, and Kusiak (2006), who used data mining to determine the sequence of assemblies that minimizes the risk of producing faulty products. Tan (2013) proposed an association rules mining system (ARMS) based on the idea of PDCA cycling. ARMS have the function of resolving problems coordinately, which can integrate process parameters in various distributed processes and discover the relationship between process parameters and product quality feature. The framework of ARMS is composed of three main modules: data warehouse platform module, association rules mining module, and association rules optimizing module.

Recently, social media, Web, and text analytics have become increasingly important. The 2015-2016 Baldrige Criteria incorporate social media into the leadership and customer focus categories. Notes in the criteria that discuss the use of social media include:

> *Use of social media may include delivering periodic messages through internal and external websites, tweets, blogging, and customer and workforce electronic forums, as well as monitoring external websites and blogs and responding, when appropriate.*
>
> *Senior leaders' focus on action also includes the actions needed to achieve your strategic objectives and may involve establishing change management plans for major organizational change or responding rapidly to significant information from social media or other input.*
>
> *In listening to the voice of the customer, you might gather and integrate various types of customer data, such as survey data, focus group findings, blog comments and data from other social media, warranty data, marketing and sales information, and complaint data that affect customers' purchasing and engagement decisions.*
>
> *Social media and Web-based technologies are a growing mode of gaining insight into how customers perceive all aspects of your involvement with them. Listening through social media may include monitoring comments on social media outlets you moderate and on those you do not control, such as wikis, online forums, and blogs other than your own.*

However, the use of analytics to process and understand such information is not explicitly addressed in the criteria; this provides a significant opportunity for quality management.

CONCLUSION

Organizations face many challenges in developing analytics capabilities, including lack of understanding of how to use analytics, competing business priorities, insufficient analytical skills, difficulty in getting good data and sharing information, and not understanding the benefits versus perceived costs of analytics studies. Successful application of analytics requires more than just knowing the tools; it requires a high-level understanding of how analytics supports an organization's competitive strategy and effective execution that crosses multiple disciplines and managerial levels. A 2011 survey concluded that business analytics is still in the "emerging stage" and is used only narrowly within business units, not across entire organizations. While analytics is used as part of the decision-making process in many organizations, most business decisions are still based on intuition (Bloomberg Businessweek Research Services and SAS 2011). Therefore, while many challenges are apparent, many more opportunities exist.

Analytical methods have been essential to quality assurance and quality management since the birth of the discipline; however, *modern* analytics opens many new opportunities for quality managers, particularly with applications of data mining and text analytics. It's not surprising that healthcare, which has dominated Baldrige in recent years, is also progressively using analytics. The introduction to a special issue on health analytics in *Health Care Management Science* (Alemi 2015) noted:

> *At Mercy Hospital in Iowa City, Iowa managers who benchmark their clinicians and pay them for performance report 6.6 percent improvements in quality of care. Access issues aside, the VA healthcare system changed from poor to one of the best in the nation through a focus on measurement and data. The use of electronic health records and its associated data have led to reductions in medication errors. Managers have used electronic health records to maximize reimbursement, in ways that have surprised insurers. Other managers report analyzing data within electronic health*

records to reduce "never events" within their facilities and to measure quality of care. The availability of data has enabled managers to go beyond traditional roles and address clinical questions. For the first time, analysts are reporting on comparative effectiveness of different healthcare interventions. … These efforts are expected to create an unprecedented shift to more use of data.

Quality professionals need to understand and develop new applications of analytics, especially predictive analytics, and begin to incorporate these approaches into their daily work. New research is needed on how quality managers use and *can use* analytics.

An *MIT/Sloan Management Review* research report (Kiron, Prentice, and Ferguson 2014) suggests three levels of analytical organizations:

- Analytically challenged: Those that rely more on intuition than data analysis, focus on cost reduction, suffer from data quality and access issue, and lack appropriate data management and analytical skills
- Analytical practitioners: Those that work to become more data driven, use analytics in operations, have "just good enough" data, and have more information needed to make decisions
- Analytical innovators: Those that have an analytics culture driven by senior leadership, are more strategic in their applications of analytics, place a high value on data, and have higher levels of analytic skills

Where does the quality and performance excellence profession want to be?

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BIOGRAPHY

James R. Evans is a professor in the Department of Operations and Business Analytics in the College of Business at the University of Cincinnati. He holds bachelor's and master's degrees in industrial engineering from Purdue, and a doctorate in industrial and systems engineering from Georgia Tech. Evans is the author or co-author of about 50 editions of college textbooks, including *Managing for Quality and Performance Excellence, 9th edition*, and *Quality & Performance Excellence: Management, Organization, and Strategy, 7th edition*, as well as *An Introduction to Six Sigma and Process Improvement, 2nd edition*, all published by Cengage Learning. In 2003, Evans and his co-author received the ASQ Philip Crosby Medal for *The Management and Control of Quality, 5th edition*. He has published close to 100 papers in the fields of operations research, operations management, and quality. Evans served as editor of the *Quality Management Journal*, and is a Fellow and past-president of the Decision Sciences Institute. He also served as an examiner for the Malcolm Baldrige National Quality Award from 1994 to 1996, senior examiner from 1997 to 1999, alumni examiner from 2000 to 2001, and judge from 2004 to 2007. Evans can be reached by email at Evansjr@ucmail.uc.edu.

Executive Briefs

Modern Analytics and the Future of Quality and Performance Excellence (pp. 6–17). James R. Evans, University of Cincinnati

Applications of analytics have grown dramatically over the last decade, particularly in industries such as business and healthcare. Many organizations are using analytics strategically to make better decisions and improve customer and shareholder value. Analytics is changing how organizations manage. That is, tools and techniques of modern analytics are used in a variety of organization types to improve the management of customer relationships, financial and marketing activities, supply chains, and other areas. Research also suggests that organizations are overwhelmed by data and have difficulty determining how to use their data to achieve business results.

The importance of modern analytics is becoming recognized in the Baldrige Criteria and represents a noteworthy opportunity for quality managers, executives who pursue performance excellence, and academic researchers. But despite the sizeable amount of activity surrounding analytics in business, the quality profession has lagged behind analytic trends, and many opportunities exist in quality management activities for using analytics.

The successful application of analytics requires more than just knowing the tools; it requires a high-level understanding of how analytics supports an organization's competitive strategy and effective execution that crosses multiple disciplines and managerial levels. Quality professionals must understand and develop new applications of analytics, and begin to incorporate these approaches into their daily work.

SEM of Service Quality to Predict Overall Patient Satisfaction in Medical Clinics: A Case Study (pp. 18–36). Dana M. Johnson, Michigan Technological University, and Roberta S. Russell, Virginia Polytechnic Institute and State University

Patient satisfaction is an integral part of quality of care for hospitals, as well as clinics and other healthcare settings. While much research is available regarding patient satisfaction in an acute care hospital, a gap in the literature exists in predicting patient satisfaction for medical clinics, and in identifying and understanding the different attributes of service quality for patients who maintain a continuing relationship with a clinic or physician's office.

The research presented in this article addresses these shortcomings by analyzing patient satisfaction surveys from medical clinics of a rural Midwestern healthcare organization. The medical clinics include family practice, urgent care, and specialty clinics, totaling 18 different locations. Patient satisfaction surveys were created and administered by a third party. Structural equation modeling (SEM) was used to identify factors that impact patient satisfaction, and the information was used to: 1) gain a greater understanding of the factors that drive overall patient satisfaction in medical clinics; and 2) explore how metrics of patient satisfaction can foster continuous process improvement efforts.

Results of this study show that the business and operations strategy and related metrics must emphasize patient satisfaction and consistent service quality. Individual consumers are able to make choices that balance cost and quality. The voice of the patient allows decision makers to be informed about what is important to their customers. The results of this study support the overall strength of the relationship and predictability of patient satisfaction from the care provider service encounter.

Factors in the Path From Lean to Patient Safety: Six Sigma, Goal Specificity, and Responsiveness Capability (pp. 37–53). Kathleen L. McFadden,