CHAPTER

11 Improving Decision Making and Managing Artificial Intelligence

LEARNING OBJECTIVES

After reading this chapter, you will be able to answer the following questions.

11-1 What are the different types of decisions, and how does the decision-making process work?

11-2 How do business intelligence and business analytics support decision making?

11-3 What is artificial intelligence (AI)? How does it differ from human intelligence?

11-4 What are the major types of AI techniques and how do they benefit organizations?

11-5 How will MIS help my career?

MyLab MIS

- Discussion Questions: 11-5, 11-6, 11-7
- Hands-On MIS Projects: 11-8, 11-9, 11-10, 11-11

CHAPTER CASES

- Machine Learning Helps Akershus University Hospital Make Better Treatment Decisions
- Siemens Makes Business Processes More Visible
- Predictive Maintenance in the Oil and Gas Industry
- Can Cars Drive Themselves—And Should They?

VIDEO CASES

- How IBM's Watson Became a Jeopardy Champion
- Business Intelligence Helps the Cincinnati Zoo Work Smarter

MACHINE LEARNING HELPS AKERSHUS UNIVERSITY HOSPITAL MAKE BETTER TREATMENT DECISIONS

The healthcare industry is deluged with big data, including patient histories, clinical records, charts, and test results. Medical information is now doubling every three years and will be doubling every 73 days by 2020. How can healthcare professionals keep up with the knowledge in their field, and how can they use this knowledge to make more-informed decisions about treatment options and managing healthcare costs when there is way too much data for humans to easily analyze and absorb?

One of the many health care organizations struggling with this problem is Akershus University Hospital (Ahus), a Norwegian public university hospital serving approximately 500,000 inhabitants around Oslo, Norway, and employing 9,500 people. Ahus had amassed huge volumes of data on patients and treatments, but much of this information was in unstructured, textual reports that made it extremely difficult and time-consuming to extract meaningful information. Combing through thousands of complex clinical documents was impossible to complete manually.

Working with Capgemini consultants, Ahus is trying to solve this problem by using artificial intelligence technology in IBM Watson Explorer. IBM Watson Explorer is a *cognitive computing* platform that can analyze structured and unstructured data to uncover trends and patterns that would be difficult, if not impossible, for humans to discern. It uses natural language processing to search data expressed in everyday language like ordinary speech and machine learning algorithms to improve search results. Natural language processing technology makes it possible for a machine to understand, analyze, and derive meaning from human language. Machine learning software can identify patterns in very large databases without explicit programming, although with significant human training. IBM Watson Explorer is able to rapidly mine large volumes of data, interpret speech and text, pick up on nuances of meaning and context, answer questions, draw conclusions, and learn from its experience. It can make inferences and correlations about the content it ingests and rank potential responses for a user to select.

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The hospital's image diagnostic department wanted to improve the use of CT examinations in emergencies. Ahus used IBM Watson Explorer to analyze when its CT scans performed on pediatric patients in emergency situations fell within recommended guidelines. CT scans can be life-saving in critical circumstances, but the radiation can also be potentially harmful, so CT scans should not be overused. A large amount of Ahus's CT scan data was in text format. Ahus used Watson Explorer to gather unstructured data from more than 5,000 anonymous CT examination reports and apply machine learning and natural language processing techniques to learn how often CT scans were undertaken and the findings of those scans.

Ahus and Capgemini implemented the project over a period of seven weeks during the summer of 2016. Watson had to learn the language used in medicine and understand the context of how that language is used. Capgemini adapted the technology to the Norwegian language, and Ahus trained Watson to understand medical words and phrases. The project also created a classification schema, teaching Watson to distinguish files that reported positive scan results and those that reported negative results, and categorize the data accordingly.

After several tests, Watson Explorer attained an accuracy level of 99 percent for content classification. The final analysis confirmed that frequency of CT scanning at Ahus was at an acceptable level, and that the hospital was striking the right balance between the probability of positive gains in relation to the potential harmful effects. It would have taken a team of people months and perhaps years to analyze the same amount of data that Watson could process in minutes.

Sources: IBM Corporation. "Akershus University Hospital," and "IBM Watson Explorer," www.ibm.com, accessed June 17, 2019; and "Akershus University Hospital Optimizes the Use of CT Examinations," www.capgemini.com, accessed June 18, 2019.

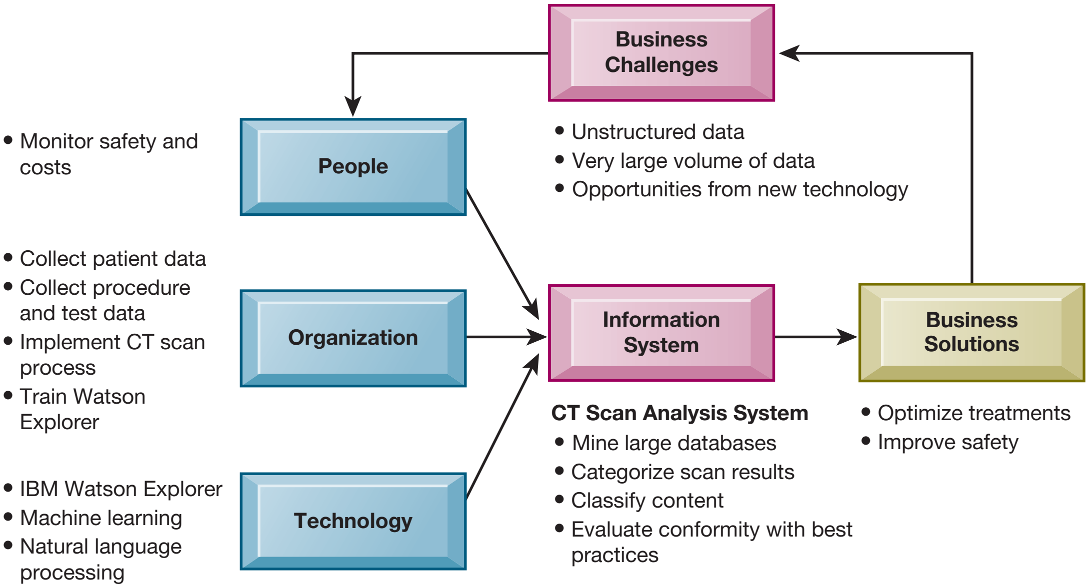
Akershus University Hospital's use of artificial intelligence techniques such as machine learning and natural language processing to determine whether its CT scans fell within recommended guidelines shows how organizational performance can benefit by using technology to facilitate the acquisition and application of knowledge. Facilitating access to knowledge, creating new knowledge, and using that knowledge to improve business processes and decision making are vital to success and survival for both private business firms and public organizations.

The chapter-opening diagram calls attention to important points raised by this case and this chapter. Like other medical facilities, Akershus University Hospital was what is termed "data rich but knowledge poor." It had vast quantities of patient and treatment data, but they were largely unstructured and difficult to analyze for information and insights. AI techniques such as machine learning and natural language processing helped Ahus obtain new insights and knowledge from thousands of CT scan records so that it could optimize treatments and ensure doctors and staff were following best practices.

Here are some questions to think about: How did using IBM Watson Explorer help Akershus University Hospital improve its knowledge? What was the impact on the hospital's business processes?

11-1 What are the different types of decisions, and how does the decision-making process work?

One of the main contributions of information systems has been to improve decision making for both individuals and groups. Decision making in businesses used to be limited to management. Today, lower-level employees are responsible for some of these decisions as information systems make information available to lower levels of the organization. But what do we mean by better decision making? How does decision making take place in businesses and other organizations? Let's take a closer look.



BUSINESS VALUE OF IMPROVED DECISION MAKING

What does it mean to a business to be able to make a better decision? What is the monetary value to a business of improved decision making? Table 11.1 measures the monetary value of improved decision making for a small manufacturing firm with $280 million in annual revenue and 140 employees. The firm has identified a number of key decisions where new system investments might improve the quality of decision making. The table provides selected estimates of annual value (in the form of cost savings or increased revenue) from improved decision making in selected areas of the business.

We can see from Table 11.1 that decisions are made at all levels of the firm and that some of these decisions are common, routine, and numerous. Although the value of improving any single decision may be small, improving hundreds of thousands of small decisions adds up to a large annual value for the business.

TYPES OF DECISIONS

Chapter 2 showed that there are different levels in an organization. Each of these levels has different information requirements for decision support and responsibility for different types of decisions (see Figure 11.1). Decisions are classified as structured, semistructured, and unstructured.

TABLE 11.1

Business Value of Enhanced Decision Making

Example Decision Value	Decision Maker	Number of Annual Decisions	Estimated Value to Firm of a Single Improved Decision	Annual
Allocate support to most valuable customers	Accounts manager	12	$100,000	$1,200,000
Predict call center daily demand	Call center management	4	$150,000	$600,000
Decide parts inventory levels daily	Inventory manager	365	$5,000	$1,825,000
Identify competitive bids from major suppliers	Senior management	1	$2,000,000	$2,000,000
Schedule production to fill orders	Manufacturing manager	150	$10,000	$1,500,000
Allocate labor to complete a job	Production floor manager	100	$4,000	$400,000

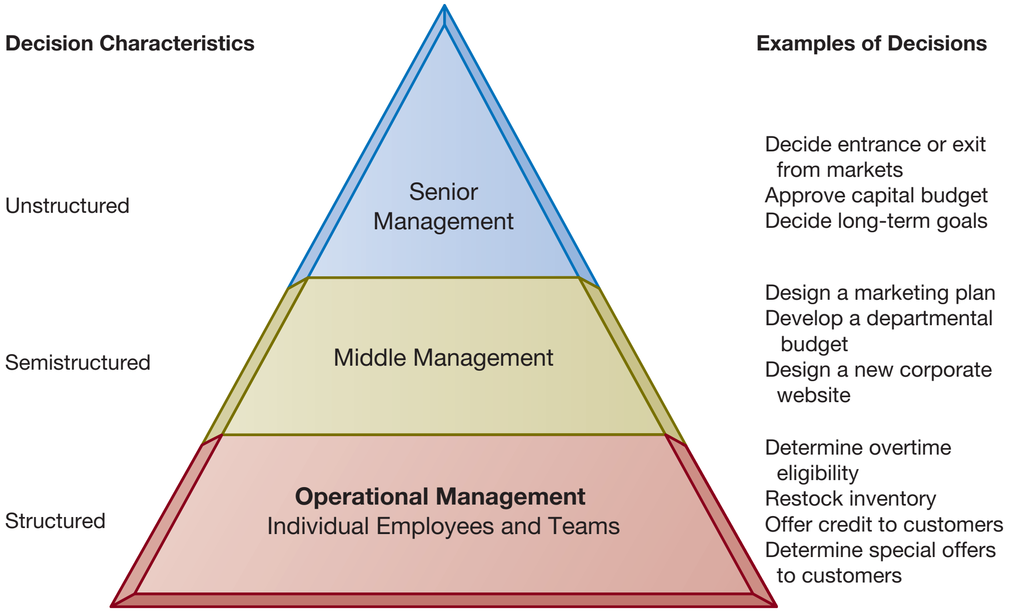


Figure 11.1 Information Requirements of Key Decision-Making Groups in a Firm.
Senior managers, middle managers, operational managers, and employees have different types of decisions and information requirements.

Unstructured decisions are those in which the decision maker must provide judgment, evaluation, and insight to solve the problem. Each of these decisions is novel, important, and not routine, and there is no well-understood or agreed-on procedure for making them.

Structured decisions, by contrast, are repetitive and routine, and they involve a definite procedure for handling them so that they do not have to be treated each time as if they were new. Many decisions have elements of both types and are **semistructured decisions**, when only part of the problem has a clear-cut answer provided by an accepted procedure. In general, structured decisions are more prevalent at lower organizational levels, whereas unstructured problems are more common at higher levels of the firm.

Senior executives face many unstructured decision situations, such as establishing the firm's five-year or ten-year goals or deciding new markets to enter. Answering the question, "Should we enter a new market?" would require access to news, government reports, and industry views as well as high-level summaries of firm performance. But the answer would also require senior managers to use their own best judgment and poll other managers for their opinions.

Middle management faces more structured decision scenarios, but their decisions may include unstructured components. A typical middle-level management decision might be "Why is the reported order fulfillment showing a decline over the past six months at a distribution center in Minneapolis?" This middle manager could obtain a report from the firm's enterprise system or distribution management system on order activity and operational efficiency at the Minneapolis distribution center. This is the structured part of the decision, but before arriving at an answer, this middle manager will have to interview employees and gather more unstructured information from external sources about local economic conditions or sales trends.

Operational management and rank-and-file employees tend to make more structured decisions. For example, a supervisor on an assembly line has to decide whether an hourly paid worker is entitled to overtime pay. If the employee worked more than eight hours on a particular day, the supervisor would routinely grant overtime pay for any time beyond eight hours that was clocked on that day.

A sales account representative often has to make decisions about extending credit to customers by consulting the firm's customer database that contains credit information. If the customer met the firm's specific criteria for granting credit, the account representative would grant that customer credit to make a purchase. In both instances, the decisions are highly structured and routinely made thousands of times each day in most large firms. The answer has been programmed into the firm's payroll and accounts receivable systems.

THE DECISION-MAKING PROCESS

Making a decision is a multistep process. Simon (1960) described four stages in decision making: intelligence, design, choice, and implementation (see Figure 11.2). These stages correspond to the four steps in problem solving used throughout this book.

Intelligence consists of discovering, identifying, and understanding the problems occurring in the organization—why the problem exists, where, and what effects it is having on the firm. **Design** involves identifying and exploring various solutions to the problem. **Choice** consists of choosing among solution alternatives. **Implementation** involves making the chosen alternative work and continuing to monitor how well the solution is working.

What happens if the solution you have chosen does not work? Figure 11.2 shows that you can return to an earlier stage in the decision-making process and repeat it if necessary. For instance, in the face of declining sales, a sales management team may decide to pay the sales force a higher commission for making more sales to spur on the sales effort. If this does not increase sales, managers would need to investigate whether the problem stems from poor product design, inadequate customer support, or a host of other causes that call for a different solution.

HIGH-VELOCITY AUTOMATED DECISION MAKING

Today, many decisions organizations make are not made by managers or any humans. For instance, when you enter a query in Google's search engine, Google's computer system has to decide which URLs to display in about half a second on average (500 milliseconds). High-frequency trading programs at electronic stock exchanges in the

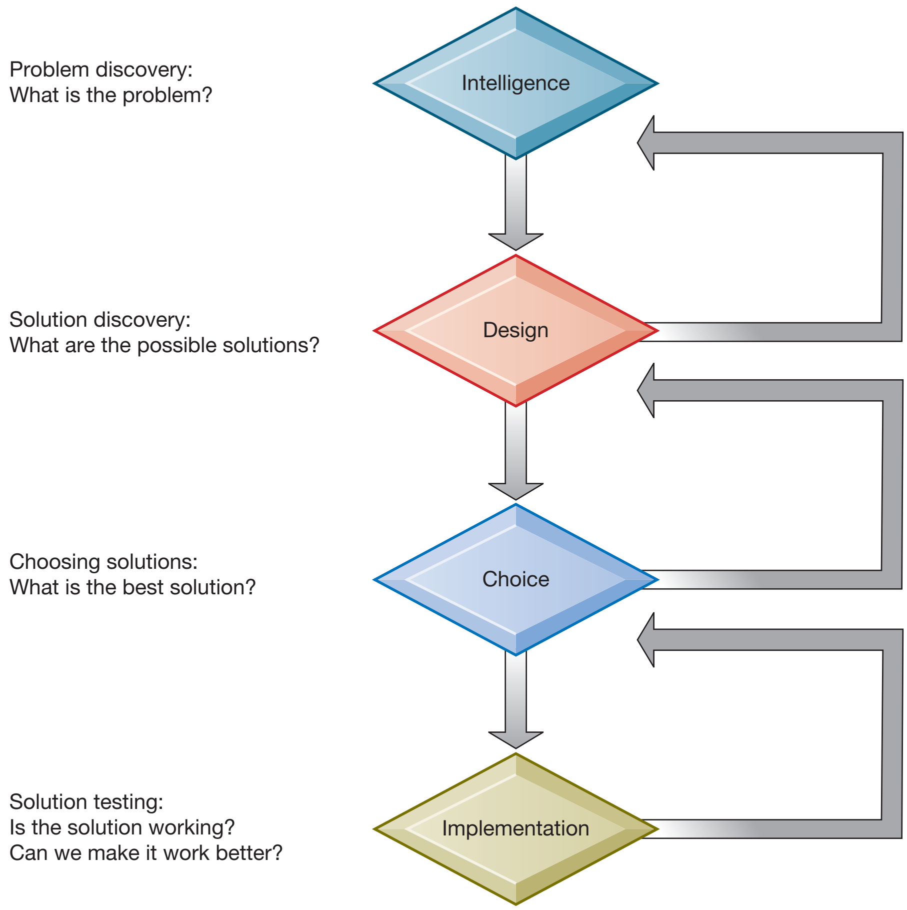


Figure 11.2
Stages in Decision Making.
The decision-making process can be broken down into four stages.

TABLE 11.2

Qualities of Decisions and the Decision-Making Process

Quality Dimension	Description
Accuracy	Decision reflects reality
Comprehensiveness	Decision reflects a full consideration of the facts and circumstances
Fairness	Decision faithfully reflects the concerns and interests of affected parties
Speed (efficiency)	Decision making is efficient with respect to time and other resources, including the time and resources of affected parties, such as customers
Coherence	Decision reflects a rational process that can be explained to others and made understandable
Due process	Decision is the result of a known process and can be appealed to a higher authority

United States execute their trades within nanoseconds. Humans are eliminated from the decision chain because they are too slow.

In these high-speed automated decisions, the intelligence, design, choice, and implementation parts of the decision-making process are captured by computer algorithms that precisely define the steps to be followed to produce a decision. The people who wrote the software identified the problem, designed a method for finding a solution, defined a range of acceptable solutions, and implemented the solution. In these situations, organizations are making decisions faster than managers can monitor or control, and great care needs to be taken to ensure the proper operation of these systems to prevent significant harm.

QUALITY OF DECISIONS AND DECISION MAKING

How can you tell whether a decision has become better or the decision-making process has improved? Accuracy is one important dimension of quality; in general, we think decisions are better if they accurately reflect the real-world data. Speed is another dimension; we tend to think that the decision-making process should be efficient, even speedy. For instance, when you apply for car insurance, you want the insurance firm to make a fast and accurate decision. However, there are many other dimensions of quality in decisions and the decision-making process to consider. Which is important for you will depend on the business firm where you work, the various parties involved in the decision, and your own personal values. Table 11.2 describes some quality dimensions for decision making. When we describe how systems "improve decisions and the decision-making process" in this chapter, we are referencing the dimensions in this table.

11-2 How do business intelligence and business analytics support decision making?

Chapter 2 introduced you to different kinds of systems for supporting the levels and types of decisions we have just described. The foundation for all of these systems is a business intelligence and business analytics infrastructure that supplies data and the analytic tools for supporting decision making.

WHAT IS BUSINESS INTELLIGENCE?

"Business intelligence" (BI) is a term that hardware and software vendors and information technology consultants use to describe the infrastructure for warehousing, integrating, reporting, and analyzing data that come from the business environment.

The foundation infrastructure collects, stores, cleans, and makes available relevant data to managers. Think databases, data warehouses, data marts, Hadoop, and analytic platforms, which we described in Chapter 6. "Business analytics" (BA) is also a vendor-defined term; it focuses more on tools and techniques for analyzing and understanding data. Think OLAP (online analytical processing), statistics, models, and data mining, which we also introduced in Chapter 6.

BI and analytics are essentially about integrating all the information streams a firm produces into a single, coherent enterprise-wide set of data and then using modeling, statistical analysis, and data mining tools to make sense out of all these data so managers can make better decisions and better plans.

It is important to remember that BI and analytics are products defined by technology vendors and consulting firms. The largest five providers of these products are SAP, Oracle, IBM, SAS, and Microsoft. A number of BI and BA products now have cloud and mobile versions.

THE BUSINESS INTELLIGENCE ENVIRONMENT

Figure 11.3 gives an overview of a BI environment, highlighting the kinds of hardware, software, and management capabilities that the major vendors offer and that firms develop over time. There are six elements in this BI environment:

- **Data from the business environment:** Businesses must deal with both structured and unstructured data from many sources, including big data. The data need to be integrated and organized so that they can be analyzed and used by human decision makers.
- **Business intelligence infrastructure:** The underlying foundation of BI is a powerful database system that captures all the relevant data to operate the business. The data may be stored in transactional databases or combined and integrated into an enterprise data warehouse, series of interrelated data marts, or analytic platforms.
- **Business analytics toolset:** A set of software tools is used to analyze data and produce reports, respond to questions managers pose, and track the progress of the business by using key indicators of performance.
- **Managerial users and methods:** BI hardware and software are only as intelligent as the human beings who use them. Managers impose order on the analysis of

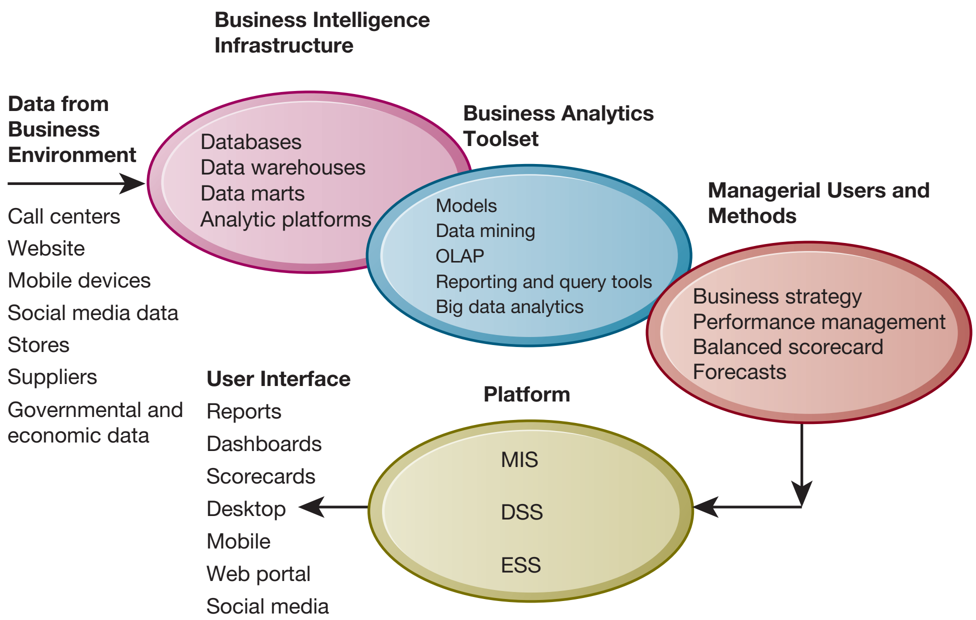


Figure 11.3
Business Intelligence and Analytics for Decision Support.
Business intelligence and analytics require a strong database foundation, a set of analytic tools, and an involved management team that can ask intelligent questions and analyze data.

data by using a variety of managerial methods that define strategic business goals and specify how progress will be measured. These include business performance management and balanced scorecard approaches that focus on key performance indicators, with special attention to competitors.

- **Delivery platform—MIS, DSS, ESS:** The results from BI and analytics are delivered to managers and employees in a variety of ways, depending on what they need to know to perform their job. MIS, decision-support systems (DSS), and executive support systems (ESS), which we introduced in Chapter 2, deliver information and knowledge to different people and levels in the firm—operational employees, middle managers, and senior executives. In the past, these systems could not easily share data and operated as independent systems. Today, business intelligence and analytics tools can integrate all this information and bring it to managers' desktops or mobile platforms.
- **User interface:** Business people often learn quicker from a visual representation of data than from a dry report with columns and rows of information. Today's business analytics software suites feature **data visualization** tools, such as rich graphs, charts, dashboards, and maps. They can deliver reports on mobile phones and tablets as well as on the firm's website. For example, Tableau Software enables nontechnical users to quickly and easily create and share customized interactive dashboards to provide business insights from a broad spectrum of data, including data from spreadsheets, corporate databases, and the web. Another example is the process mining software used by Siemens AG to visualize and analyze its business processes (see the Interactive Session on Technology).

Virtual Reality and Augmented Reality

Virtual reality (VR) systems have powerful capabilities for three-dimensional data visualization. They use interactive graphics software to create computer-generated simulations that are so close to reality that users almost believe they are participating in a real-world situation. In many virtual reality systems, the user dons special clothing, headgear, and equipment, depending on the application. The clothing contains sensors that record the user's movements and immediately transmit that information back to the computer.

Virtual reality applications are currently found in entertainment, retail, and manufacturing, where an immersive experience can help customers visualize products or

Data visualization tools facilitate creation of graphs, charts, dashboards, and maps to make it easier for users to obtain insights from data.

INTERACTIVE SESSION: TECHNOLOGY Siemens Makes Business Processes More Visible

Siemens AG is a German manufacturing conglomerate that produces systems and components for industrial automation, healthcare, energy, building, and transportation markets. The company is headquartered in Munich and Berlin, with 372,000 employees worldwide, and global revenue of €83 billion (approximately US $99 billion) in fiscal 2017. Siemens is the largest industrial manufacturing company in Europe, with branch offices abroad. This is clearly a company that prizes innovation and continuous improvement of the efficiency and quality of its business processes.

Siemens has thousands of business processes, some of which are very complex. Management was seeking better ways of making the business more efficient and turned to business process mining technology. In 2014 the company established a unit called Process DAsh (which stands for Data Analytics, smart handling) to actively support global process optimization in all Siemens divisions. It started collecting and analyzing ERP data to identify bottlenecks in its production, delivery, and payment processes using Celonis Process Mining analysis and visualization software for this purpose. Celonis partners with SAP, and its software runs on the SAP HANA in-memory database platform.

Process mining software analyzes data in enterprise application event logs to determine how business processes are actually working in order to identify bottlenecks and other areas of inefficiency so that they can be improved. The technology can analyze millions of transaction records and spot deviations from normal workflows. A push of a button produces a snapshot of an entire business process. Process DAsh used the Celonis software to take all the individual data in a large number of information systems and use them to construct logical models of existing business processes and automatically visualize them. The software documents actual processes in real time, as the sequence of events is taking place.

When process mining software is used to analyze the transaction logs of an ERP or CRM system, data visualization capabilities in the software can show users what processes are running at any given time. An organization might use process mining software to find the cause of unexpected delays in invoice processing by examining the logs of the accounts payable module in its ERP system. Users can see at a glance where inefficiencies occur through bottlenecks, unnecessary detours, and manual interventions, or where compliance issues might arise. Some process mining software, including Celonis, enables users to drill down to view the individual documents associated with a process.

Celonis has capabilities for comparing users' target operating models to the as-is process, providing an automated fit-gap analysis. Celonis analyzes root causes for deviations and performance loss, highlighting the issues that have the greatest impact on process performance. At the touch of a button, the user can see a comparison between the target and actual process and also visualize the main cause of delays and additional expenditure.

If a process model doesn't already exist, the software will try to create one automatically, sometimes using artificial intelligence techniques such as machine learning (see section 11-4). If a process model is available, the process mining software will compare it to the event log to identify discrepancies and their possible causes. For process modeling, Siemens uses a Celonis tool called Pi Conformance and Machine Learning. The software predicts which customer orders are likely to arrive late using algorithms that continuously learn from Siemens' performance.

Siemens started using Celonis analysis and visualization tools to learn how quickly it pays its suppliers. Some suppliers offer discounts for early payment. Siemens was often unable to take advantage of these discounts because it was unable to pay quickly enough. The company used process mining to analyze data from its ERP, accounting, and payment approval systems to understand why this was happening. Siemens also used process mining to study inefficiencies in the way it takes orders from and is paid by its customers (order-to-cash processes).

Before implementing the Celonis software, Siemens had to manage its business processes manually. Individual supervisors were responsible for specific processes. When things did not go as planned, such as when a machine broke down or a parts shipment arrived late, there was no easy way to determine exactly how these occurrences impacted overall operations.

There was some resistance to process mining among some long-term Siemens managers who thought they already knew how to handle processes efficiently. Lars Reinkemeyer, head of

Siemens global process mining services, was able to promote analytics adoption by identifying individuals who were receptive to process mining and enlisting them to promote the new technology. Since Siemens AG implemented process mining, it has been able to identify slowdowns in parts procurement, late product deliveries, and billing inefficiencies that were costing the company millions of dollars. Siemens AG now has over 2,500 users of Process DAsh worldwide.

Sources: Lindsay Clark, "Siemens Success Sets the Scene for Growth in Process Mining," *Computer Weekly*, April 12, 2018; Julian Baumann, "Siemens Is the World's Biggest User of Process Mining" and "Success Story: SIemens," www.celonis.com, accessed April 22, 2019; Margaret Rouse, "Process Mining Software," searchERP.com, June 30, 2017; and Ed Burns, "Siemens Uses Process Mining Software to Improve Manufacturing Visibility," SearchBusinessAnalytics.com, December 15, 2016.

CASE STUDY QUESTIONS

1. Identify the problem in this case study. What people, organization, and technology factors contributed to the problem?
2. Describe the capabilities of process mining software. Was this an effective solution? Explain your answer.
3. How did process mining change decision making at Siemens?
4. What people, organization, and technology issues need to be addressed when implementing process mining systems?

teach factory workers how to use complex equipment. Audi has used virtual reality technology in its "dealership in a briefcase" program. By donning an Oculus Rift virtual reality headset, prospective buyers can feel as if they are sitting behind the wheel of a car or opening up the trunk. The VR headset displays in 3-D exactly what you'd see if you were looking over a real-life Audi. Volkswagen Group is experimenting with virtual reality to speed up vehicle design and development and to identify potentially costly design problems earlier in the development cycle. Volkswagen has been able to cut out costly physical prototypes and replace them with immersive, 360-degree views of digitally constructed interior and exterior components of a vehicle using virtual reality HTC Vive headsets. Virtual components of a car, including interior and exterior parts such as buttons, lights, or consoles, can be switched out and replaced easily with a few lines of software code during the design process.

Augmented reality (AR) is a related technology for enhancing visualization by overlaying digital data and images onto a physical real-world environment. The digital technology provides additional information to enhance the perception of reality, making the surrounding real world of the user more interactive and meaningful. The yellow first-down markers shown on televised football games are examples of augmented reality as are medical procedures like image-guided surgery, where data acquired from computerized tomography (CT) and magnetic resonance imaging (MRI) scans or from ultrasound imaging are superimposed on the patient in the operating room. Other industries where AR has caught on include military training, engineering design, robotics, and consumer design. For example, Newport News Shipbuilding, which designs and builds US Navy aircraft carriers, uses AR to inspect a ship near the end of the manufacturing process. By seeing the final design superimposed on the ship, engineers have reduced inspection time by 96 percent—from 36 hours to only 90 minutes (Porter and Heppelmann, 2017).

BUSINESS INTELLIGENCE AND ANALYTICS CAPABILITIES

BI and analytics promise to deliver correct, nearly real-time information to decision makers, and the analytic tools help them quickly understand the information and take action. There are six analytic functionalities that BI systems deliver to achieve these ends:

Production reports: These are predefined reports based on industry-specific requirements (see Table 11.3).

TABLE 11.3

Examples of Predefined Business Intelligence Production Reports

Business Functional Area	Production Reports
Sales	Sales forecasts, sales team performance, cross selling, sales cycle times
Service/Call Center	Customer satisfaction, service cost, resolution rates, churn rates
Marketing	Campaign effectiveness, loyalty and attrition, market basket analysis
Procurement and Support	Direct and indirect spending, off-contract purchases, supplier performance
Supply Chain	Backlog, fulfillment status, order cycle time, bill of materials analysis
Financials	General ledger, accounts receivable and payable, cash flow, profitability
Human Resources	Employee productivity, compensation, workforce demographics, retention

Parameterized reports: Users enter several parameters to filter data and isolate impacts of parameters. For instance, you might want to enter region and time of day to understand how sales of a product vary by region and time. If you were Starbucks, you might find that customers in the eastern United States buy most of their coffee in the morning, whereas in the northwest customers buy coffee throughout the day. This finding might lead to different marketing and ad campaigns in each region. (See the discussion of pivot tables later in this section.)

Dashboards/scorecards: These are visual tools for presenting performance data users define.

Ad hoc query/search/report creation: This allows users to create their own reports based on queries and searches.

Drill down: This is the ability to move from a high-level summary to a more detailed view.

Forecasts, scenarios, models: These include capabilities for linear forecasting, what-if scenario analysis, and data analysis, using standard statistical tools.

Predictive Analytics

An important capability of BI analytics is the ability to model future events and behaviors, such as the probability that a customer will respond to an offer to purchase a product. **Predictive analytics** use statistical analysis, data mining techniques, historical data, and assumptions about future conditions to predict future trends and behavior patterns. Variables that can be measured to predict future behavior are identified. For example, an insurance company might use variables such as age, gender, and driving record as predictors of driving safety when issuing auto insurance policies. A collection of such predictors is combined into a predictive model for forecasting future probabilities with an acceptable level of reliability. Georgia State and other colleges and universities are using predictive analytics to examine millions of student academic and personal records to spot students in danger of dropping out.

FedEx has been using predictive analytics to develop models that predict how customers will respond to price changes and new services, which customers are most at risk of switching to competitors, and how much revenue will be generated by new storefront or drop-box locations. The accuracy rate of FedEx's predictive analytics system ranges from 65 to 90 percent.

Predictive analytics are being incorporated into numerous BI applications for sales, marketing, finance, fraud detection, and healthcare. One of the best-known applications is credit scoring, which is used throughout the financial services industry. When you apply for a new credit card, scoring models process your credit history, loan application, and purchase data to determine your likelihood of making future credit payments on time. Healthcare insurers have been analyzing data for years to identify which patients are most likely to generate high costs.

Many companies employ predictive analytics to predict response to marketing campaigns and other efforts to cultivate customers. By identifying customers more likely to respond, companies can lower their marketing and sales costs by focusing their resources on customers who have been identified as more promising. For instance, Slack Technologies, which provides cloud-based team collaboration tools and services for 10 million daily active users, uses predictive analytics to identify customers who are most likely to use its products frequently and upgrade to its paid services.

Big Data Analytics

Predictive analytics are starting to use big data from both private and public sectors, including data from social media, customer transactions, and output from sensors and machines. In e-commerce, many online retailers have capabilities for making personalized online product recommendations to their website visitors to help stimulate purchases and guide their decisions about what merchandise to stock. Most of these product recommendations, however, are based on the behaviors of similar groups of customers, such as those with incomes under $50,000 or whose ages are between 18 and 25. Now some firms are starting to analyze the tremendous quantities of online and in-store customer data they collect along with social media data to make these recommendations more individualized. These efforts are translating into higher customer spending and retention rates. Table 11.4 provides examples of companies using big data analytics.

In the public sector, big data analytics are driving the movement toward smart cities, which make intensive use of digital technology and public record data stores to make better decisions about running cities and serving their residents. Municipalities are capturing more data through sensors, location data from mobile phones, and

TABLE 11.4

What Big Data Analytics Can Do

Organization	Big Data Capabilities
Tesco	One of the largest retailers in the world, the firm set up its own subsidiary, Dunnhumby, to provide itself and other retailers with expertise using big data analytics to gain customer insights, reduce inventory waste, and optimize their use of energy. Tesco has detailed data on more than 350 million customers in 28 different countries.
Standard Bank	Uses big data and IBM Watson to speed handling of customer queries, allowing it to identify customers quickly so they can respond in faster time.
German World Cup Soccer Team	Analyzed very large amounts of video and numeric data about individual player and team performance on itself and competing teams and then used what it had learned to improve how it played and to capitalize on competitors' strengths and weaknesses. Superior use of big data analytics helped the team win the 2014 World Cup.
eHarmony	Online dating website analyzes personal and behavioral data provided by 20 million users to match couples based on features of compatibility found in thousands of successful relationships. Processes more than 3.5 million matches daily.

targeted smartphone apps. Predictive modeling programs now inform utility management, transportation operation, healthcare delivery, and public safety. For example, irrigation systems built into the city of Barcelona's parks monitor soil moisture and turn on sprinklers when water is needed. The city expects to reduce its water bill by 25 percent per year after installing sensors in local parks.

Operational Intelligence and Analytics

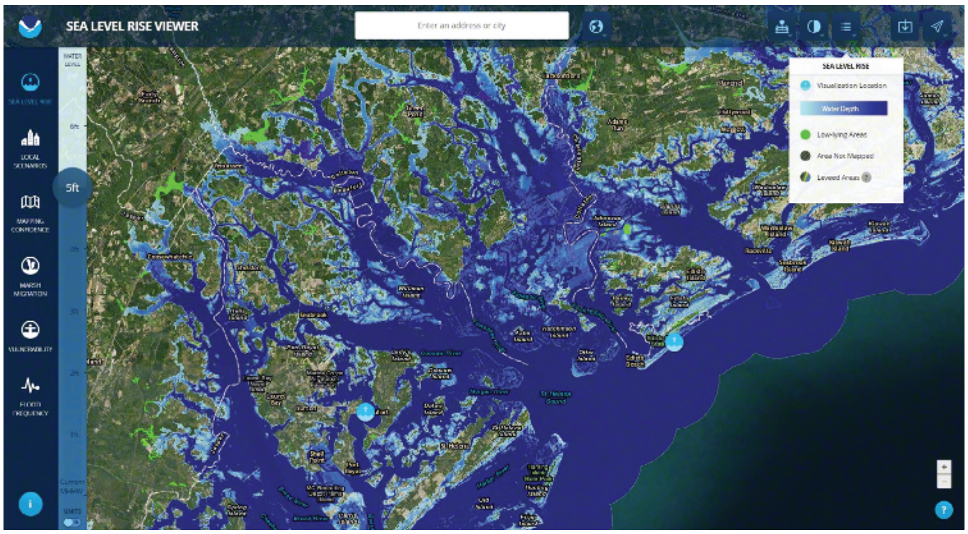
Many decisions deal with how to run cities and businesses on a day-to-day basis. These are largely operational decisions, and this type of business activity monitoring is called **operational intelligence**. The Internet of Things is creating huge streams of data from web activities, smartphones, sensors, gauges, and monitoring devices that can be used for operational intelligence about activities inside and outside the organization. Software for operational intelligence and analytics enables organizations to analyze these streams of big data as they are generated in real time. Companies can set trigger alerts on events or have them fed into live dashboards to help managers with their decisions.

An example of operational intelligence is the use of data generated by sensors on trucks, trailers, and intermodal containers owned by Schneider National, one of North America's largest truckload, logistics, and intermodal services providers. The sensors monitor location, driving behaviors, fuel levels, and whether a trailer or container is loaded or empty. Data from fuel tank sensors help Schneider identify the optimal location at which a driver should stop for fuel based on how much is left in the tank, the truck's destination, and fuel prices en route. Schneider's sensors also capture hard braking in a moving truck and relay the data to corporate headquarters, where the data are tracked in dashboards monitoring safety metrics. The event initiates a conversation between the driver and that person's supervisor.

The Interactive Session on Organizations describes how oil and gas companies are using operational intelligence for preventive maintenance, which can predict which pieces of equipment or infrastructure might shortly break down so that maintenance can be scheduled before failure occurs.

Location Analytics and Geographic Information Systems

Big data analytics include **location analytics**, the ability to gain business insight from the location (geographic) component of data, including location data from mobile phones, output from sensors or scanning devices, and data from maps. For example, location analytics might help a marketer determine which people to target with mobile ads about nearby restaurants and stores or quantify the impact of mobile ads



The US National Oceanic and Atmospheric Administration (NOAA) Office for Coastal Management provides a web mapping tool to visualize community-level impacts from coastal flooding or sea level rise up to 6 feet above average high tides. Photo simulations of how future flooding might impact local landmarks are also provided, as well as data related to water depth, connectivity, flood frequency, socioeconomic vulnerability, and wetland loss and migration.

Source: Courtesy of U.S. National Oceanic and Atmospheric Administration (NOAA) Office for Coastal Management.

INTERACTIVE SESSION: ORGANIZATIONS

Predictive Maintenance in the Oil and Gas Industry

In a number of industries, improving the productivity of existing assets by even a single percentage point can generate significant benefits. This is true of the oil and gas sector, which is deeply affected by unplanned downtime, when equipment cannot operate because of a malfunction. A single unproductive day on a platform can cost a liquefied natural gas (LNG) facility as much as $25 million, and an average midsized LNG facility experiences about five down days a year. That's $125 to $150 million lost. Minimizing downtime is critical, especially considering declining revenues from lower energy prices. Big data analytics can help.

Sensors in oil fields and in oil and natural gas pipelines produce a vast amount of data that can be analyzed for predictive maintenance. McKinsey & Company estimates that a typical offshore production platform can have more than 40,000 data tags. Energy companies have been using oil field sensors to monitor real-time operations status, and now they are starting to use IoT data to predict equipment failure and address issues before they become costly problems. Physical inspection of equipment in remote locations is typically an expensive process. This lack of visibility can lead to equipment failure and costly unscheduled maintenance and nonproductive time, as well as oil spills, leakages, or accidents resulting from failing equipment.

Predictive maintenance tools evaluate the condition of operational equipment and predict its maintenance requirements in order to achieve optimum performance and prevent malfunction. They use automated condition monitoring and advanced data analytics to gather vital equipment statistics such as vibration, temperature, sound, and electric current, comparing them with historical records of similar equipment to detect signs of deterioration. The insights gained from predictive maintenance programs enable decision makers to schedule maintenance activities without disrupting routine production operations and to determine which repairs are the highest priority.

British oil and gas company BP worked with General Electric (GE) in 2015 to equip 650 of its thousands of oil wells with GE sensors linked to GE's Predix cloud platform. Predix provides services for developing and running IoT applications that collect data from industrial sensors and analyze the data in the cloud, providing real-time information to schedule maintenance checks, improve machine efficiency, and reduce downtime. Each BP well was outfitted with 20 to 30 sensors to measure pressure and temperature, transmitting 500,000 data points to the Predix cloud every 15 seconds. BP hopes to use the data to predict well flows and the useful life of each well and ultimately to obtain an enterprise-wide view of its oil fields' performance.

The BP partnership with GE recently produced an application called Plant Operations Advisor (POA) that will further improve the efficiency, reliability, and safety of BP's oil and gas production operations. Plant Operations Advisor will prevent unplanned downtime by helping engineering teams respond quickly to problems as they occur in real time. BP first used Plant Operations Advisor to help manage the performance of one of its platforms in the Gulf of Mexico and will soon deploy this tool to other BP facilities around the world.

GE identified pipeline risk management as a major challenge for the oil and gas industry. There are 2 million miles of transmission pipe throughout the globe, moving liquid oil or gas from its point of extraction to refining, processing, or market. About 55 percent of transmission pipeline in the United States was installed before 1970. Pipeline spills are not frequent, but when they occur, they create serious economic and environmental damage as well as bad publicity for pipeline operators and energy companies. Pipeline operators are always anxious to know where their next rupture will be, but they typically lacked the data to measure pipeline fitness.

GE developed a pipeline-management software suite for accessing, managing, and integrating critical data for the safe management of pipelines, including a risk assessment tool to monitor aging infrastructure. GE's risk-assessment solution combines internal and external factors (such as flooding) to provide an accurate, up-to-the minute visual representation of where risk exists in a pipeline. This risk assessment tool enables pipeline operators to make real-time decisions about where field service crews should be deployed along the pipeline.

Weather has a sizable impact on risk for pipelines in areas prone to seismic activity, waterways, and washouts. Checking weather patterns along thousands of miles of pipe for rain or flood zones, and integrating those data with other complex pipeline data sets is difficult to perform manually.

But by bringing all relevant data together in one place, GE Predix gives pipeline operators easier access to information to help them address areas with the greatest potential impact.

Royal Dutch Shell PLC is using the Microsoft Azure cloud platform and the C3 IoT platform-as-a-service (PaaS) application development platform to monitor and predict where and when maintenance is needed for compressors, valves, and other equipment. Predictive maintenance applications built with these tools are moving into production. One handles equipment performing coal seam gas (gas collected from unmined coal seams) production in Australia, while another helps detect anomalies in downstream valves. Shell is now trying to deploy predictive maintenance technology at tens and even hundreds of thousands of sites and over one million pieces of individual equipment.

Sources: www.predix.io, accessed May 20, 2019; "BP and GE Announce New Offshore Digital Technology with Plans to Deploy Globally," www.powergenadvancement.com, accessed June 12, 2019; "Predictive Maintenance Gains Greater Significance in Oil and Gas Industry," *Oil & Gas Engineering*, May 24, 2019; Caroline Donnelly, "AI and Machine Learning Help to Power Shell's Multi-Decade Digital Transition," *Computer Weekly Nordic*, November 2018–January 2019; Steven Norton, "Shell Announces Plans to Deploy Applications at Scale," *CIO Journal*, September 20, 2019; Laura Winig, "GE's Big Bet on Data and Analytics," *MIT Sloan Management Review,* February 2016; and Holly Lugassy, "GE Leverages Pivotal Cloud Foundry to Build Predix, First Cloud for Industry," CloudFoundry.org, May 11, 2016.

CASE STUDY QUESTIONS

1. Why is predictive maintenance so important in the oil and gas industry? What problems does it solve?
2. What is the role of the Internet of Things (IoT) and Big Data analytics in predictive maintenance?
3. How did BP and Royal Dutch Shell's predictive maintenance applications change business operations and decision making?
4. Give an example of how predictive maintenance systems could be used in another industry.

on in-store visits. Location analytics would help a utility company identify, view, and measure outages and their associated costs as related to customer location to help prioritize marketing, system upgrades, and customer service efforts. UPS's package tracking and delivery routing systems, described in Chapter 1, use location analytics, as does an application Starbucks uses to determine where to open new stores. (The system identifies geographic locations that will produce a high sales-to-investment ratio and per-store sales volume.)

The Starbucks and utility company applications are examples of **geographic information systems (GIS)**. GIS provide tools to help decision makers visualize problems that benefit from mapping. GIS software ties location data about the distribution of people or other resources to points, lines, and areas on a map. Some GIS have modeling capabilities for changing the data and automatically revising business scenarios. GIS might be used to help state and local governments calculate response times to natural disasters and other emergencies, to help banks identify the best locations for new branches or ATM terminals, or to help police forces pinpoint locations with the highest incidence of crime.

BUSINESS INTELLIGENCE USERS

Figure 11.4 shows that more than 80 percent of the audience for BI consists of casual users. Senior executives tend to use BI to monitor firm activities by using visual interfaces such as dashboards and scorecards. Middle managers and analysts are much more likely to be immersed in the data and software, entering queries and slicing and dicing the data along different dimensions. Operational employees will, along with customers and suppliers, be looking mostly at prepackaged reports.

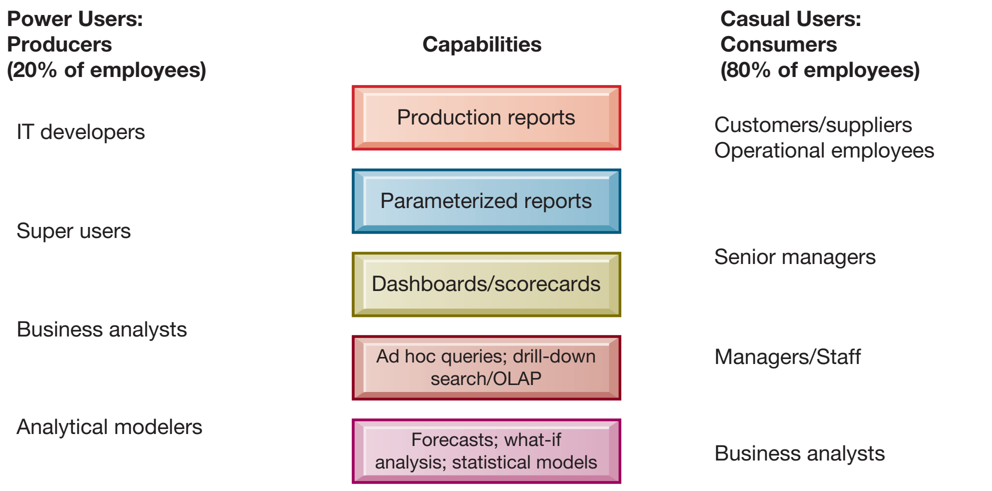


Figure 11.4
Business Intelligence Users.
Casual users are consumers of BI output, whereas intense power users are the producers of reports, new analyses, models, and forecasts.

Support for Semistructured Decisions

Many BI prepackaged production reports are MIS reports supporting structured decision making for operational and middle managers. We described operational and middle management, and the systems they use, in Chapter 2. Some managers, however, are super users and keen business analysts who want to create their own reports; they use more sophisticated analytics and models to find patterns in data, to model alternative business scenarios, or to test specific hypotheses. DSS are the BI delivery platform for this category of users, with the ability to support semistructured decision making.

DSS rely more heavily on modeling than MIS, using mathematical or analytical models to perform what-if or other kinds of analysis. What-if analysis, working forward from known or assumed conditions, allows the user to vary certain values to test results to predict outcomes if changes occur in those values. What happens if we raise product prices by 5 percent or increase the advertising budget by $1 million? **Sensitivity analysis** models ask what-if questions repeatedly to predict a range of outcomes when one or more variables are changed multiple times (see Figure 11.5). Backward sensitivity analysis helps decision makers with goal seeking: If I want to sell 1 million product units next year, how much must I reduce the price of the product?

Chapter 6 described multidimensional data analysis and OLAP as one of the key business intelligence technologies. Spreadsheets have a similar feature for multidimensional analysis, called a **pivot table**, which superuser managers and analysts employ to identify and understand patterns in business information that may be useful for semistructured decision making.

Total fixed costs	**19000**					
Variable cost per unit	**3**					
Average sales price	**17**					
Contribution margin	**14**					
Break-even point	**1357**					
				Variable Cost per Unit		
Sales	**1357**	**2**	**3**	**4**	**5**	**6**
Price	**14**	1583	1727	1900	2111	2375
	15	1462	1583	1727	1900	2111
	16	1357	1462	1583	1727	1900
	17	1267	1357	1462	1583	1727
	18	1188	1267	1357	1462	1583

Figure 11.5
Sensitivity Analysis.
This table displays the results of a sensitivity analysis of the effect of changing the sales price of a necktie and the cost per unit on the product's break-even point. It answers the question, "What happens to the break-even point if the sales price and the cost to make each unit increase or decrease?"

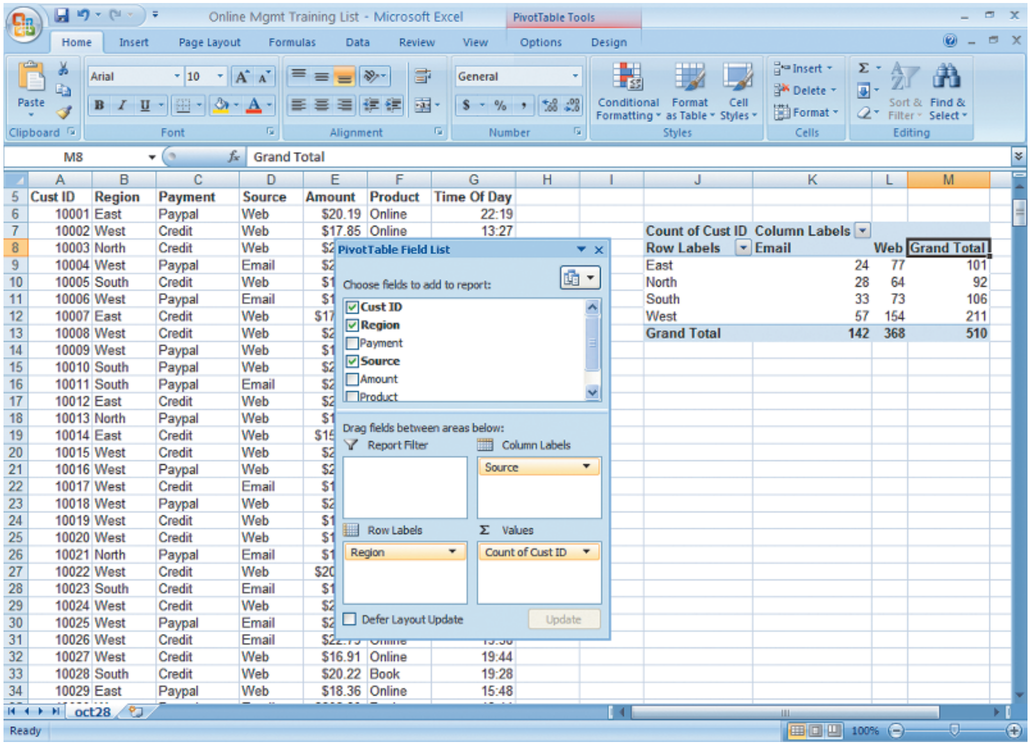


Figure 11.6
A Pivot Table That Examines Customer Regional Distribution and Advertising Source.

In this pivot table, we can examine where an online training company's customers come from in terms of region and advertising source.

Source: Courtesy of Microsoft Corporation

Figure 11.6 illustrates a Microsoft Excel pivot table that examines a large list of order transactions for a company selling online management training videos and books. It shows the relationship between two dimensions: the sales region and the source of contact (web banner ad or email) for each customer order. It answers the question of whether the source of the customer makes a difference in addition to region. The pivot table in this figure shows that most customers come from the West and that banner advertising produces most of the customers in all the regions.

One of the Hands-On MIS projects for this chapter asks you to use a pivot table to find answers to a number of other questions by using the same list of transactions for the online training company as we used in this discussion. The complete Excel file for these transactions is available in MyLab MIS. We have a Learning Track on creating pivot tables by using Excel.

In the past, much of this modeling was done with spreadsheets and small standalone databases. Today these capabilities are incorporated into large enterprise BI systems, and they can analyze data from large corporate databases. BI analytics include tools for intensive modeling. Such capabilities help Progressive Insurance identify the best customers for its products. Using widely available insurance industry data, Progressive defines small groups of customers, or cells, such as motorcycle riders aged 30 or older with college educations, credit scores over a certain level, and no accidents. For each cell, Progressive performs a regression analysis to identify factors most closely correlated with the insurance losses that are typical for this group. It then sets prices for each cell and uses simulation software to test whether this pricing arrangement will enable the company to make a profit. These analytic techniques make it possible for Progressive to insure customers profitably in traditionally high-risk categories that other insurers would have rejected.

Decision Support for Senior Management: The Balanced Scorecard and Enterprise Performance Management

BI delivered in the form of ESS helps senior executives focus on the most important performance information that affects the overall profitability and success of the firm. A leading methodology for understanding this important information a firm's

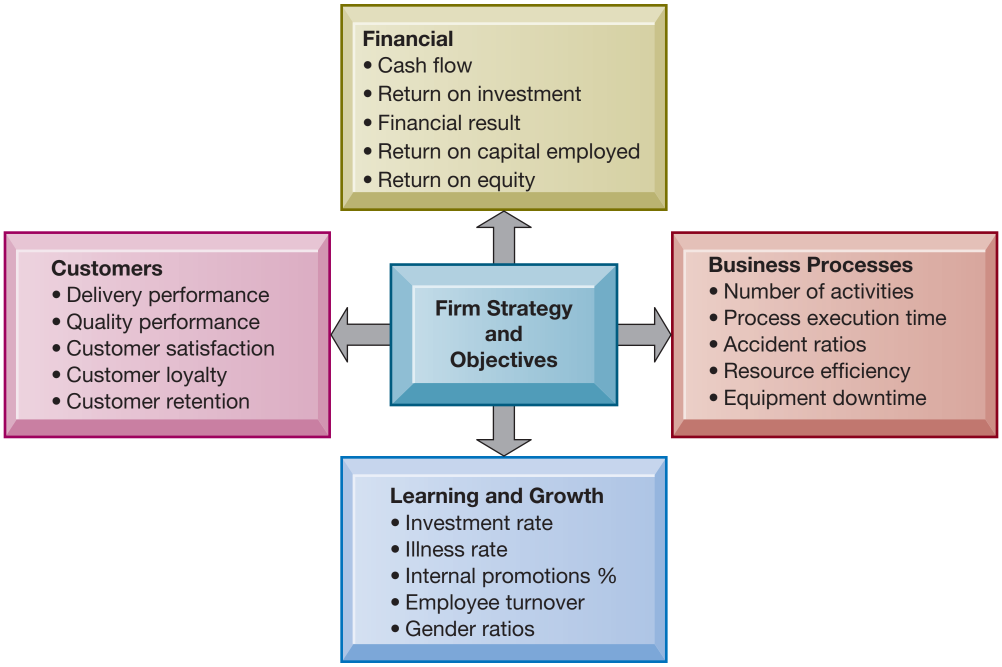


Figure 11.7
The Balanced Scorecard Framework.
In the balanced scorecard framework, the firm's strategic objectives are operationalized along four dimensions: financial, business process, customer, and learning and growth. Each dimension is measured, using several KPIs.

executives need is called the **balanced scorecard method**. The balanced scorecard is a framework for operationalizing a firm's strategic plan by focusing on measurable outcomes of four dimensions of firm performance: financial, business process, customer, and learning and growth (see Figure 11.7).

Performance of each dimension is measured using **key performance indicators (KPIs)**, which are the measures proposed by senior management for understanding how well the firm is performing along any given dimension. For instance, one key indicator of how well an online retail firm is meeting its customer performance objectives is the average length of time required to deliver a package to a consumer. If your firm is a bank, one KPI of business process performance is the length of time required to perform a basic function such as creating a new customer account.

The balanced scorecard framework is thought to be balanced because it causes managers to focus on more than just financial performance. In this view, financial performance is past history—the result of past actions—and managers should focus on the things they can influence today, such as business process efficiency, customer satisfaction, and employee training. Once consultants and senior executives develop a scorecard, the next step is automating a flow of information to executives and other managers for each of the key performance indicators.

Another closely related management methodology is **business performance management (BPM)**. Originally defined by an industry group in 2004 (led by the same companies that sell enterprise and database systems, such as Oracle, SAP, and IBM), BPM attempts to translate a firm's strategies (e.g., differentiation, low-cost producer, market share growth, and scope of operation) systematically into operational targets. Once the strategies and targets are identified, a set of key performance indicators is developed to measure progress toward the targets. The firm's performance is then measured with information drawn from the firm's enterprise database systems.

Corporate data for contemporary ESS are supplied by the firm's existing enterprise applications (enterprise resource planning, supply chain management, and customer relationship management). ESS also provide access to news services, financial market databases, economic information, and whatever other external data senior executives require. ESS have significant **drill-down** capabilities if managers need more detailed views of data.

Well-designed ESS help senior executives monitor organizational performance, track activities of competitors, recognize changing market conditions, and identify problems and opportunities. Employees lower down in the corporate hierarchy also use these systems to monitor and measure business performance in their areas of responsibility. For these and other business intelligence systems to be truly useful, the information must be actionable—readily available and easy to use when making decisions. If users have difficulty identifying critical metrics within the reports they receive, employee productivity and business performance will suffer.

11-3 What is artificial intelligence (AI)? How does it differ from human intelligence?

"Intelligent" techniques are often described as **artificial intelligence (AI)**. There are many definitions of artificial intelligence. In the most ambitious vision, AI involves the attempt to build computer systems that think and act like humans. Humans see, hear, and communicate with natural languages, make decisions, plan for the future, achieve goals, perceive patterns in their environments, and learn, among many other capabilities. Humans also love, hate, and choose what objectives they want to pursue. These are the foundations of what is called "human intelligence" and what is called "common sense" or generalized intelligence.

So far the "Grand Vision" of AI remains a distant dream: there are no computer programs that have demonstrated generalized human intelligence or common sense. Human intelligence is vastly more complex than the most sophisticated computer programs and covers a broader range of activities than is currently possible with "intelligent" computer systems and devices.

A narrow definition of artificial intelligence is far more realistic and useful. Stripped of all the hyperbole, artificial intelligence programs are like all computer programs: They take data input from the environment, process that data, and produce outputs. AI programs differ from traditional software programs in the techniques they use to input and process data. AI systems today can perform many tasks that would be impossible for humans to accomplish, and can equal or come close to humans in tasks such as interpreting CT scans, recognizing faces and voices, playing games like chess or Go, or besting human experts in certain well-defined tasks. In many industries they are transforming how business is done, where people are employed, and how they do their jobs.

EVOLUTION OF AI

In the last decade, significant progress has been made within this limited vision of AI. The major forces driving the rapid evolution of AI are the development of Big Data databases generated by the Internet, e-commerce, the Internet of Things, and social media. Secondary drivers include the drastic reduction in the cost of computer processing and the growth in the power of processors. And finally, the growth of AI has relied on the refinement of algorithms by tens of thousands of AI software engineers and university AI research centers, along with significant investment from business and governments. There have been few fundamental conceptual breakthroughs in AI in this period, or in understanding how humans think. Many of the algorithms and statistical techniques were developed decades earlier but could not be implemented and refined on such a large scale as is currently possible.

Progress has been significant: Image recognition programs have gone from 25 percent error rates down to less than 3 percent in 2018; natural language speech recognition errors have dropped from 15 percent to 6 percent; and in translation among common languages, Google's Translate program achieves about 85 percent accuracy compared to humans. These advances have made possible personal assistants like Siri (Apple), Alexa (Amazon), Cortana (Microsoft), and Now (Google), as well as speech-activated systems in automobiles.

In a famous 1950 paper, computer scientist Alan Turing defined an artificially intelligent computer program as one that a human could have a conversation with and not be able to tell it was a computer (Turing, 1950). We still cannot have a genuine conversation with a computer AI system because it has no genuine understanding of the world, no common sense, and does not truly understand humans. Nevertheless, AI systems can be enormously helpful to humans and business firms.

11-4 What are the major types of AI techniques and how do they benefit organizations?

Artificial intelligence is a family of programming techniques and technologies, each of which has advantages in select applications. Table 11.5 describes the major types of AI: expert systems, machine learning, neural networks, deep learning, genetic algorithms, natural language processing, computer vision systems, robotics, and intelligent agents. Let's take a look at each type of AI and understand how it is used by businesses and other organizations.

EXPERT SYSTEMS

Expert systems were developed in the 1970s and were the first large-scale applications of AI in business and other organizations. They account for an estimated 20 percent of all AI systems today. Expert systems capture the knowledge of individual experts in an organization through in-depth interviews, and represent that knowledge as sets of rules. These rules are then converted into computer code in the form of IF-THEN rules. Such programs are often used to develop apps that walk users through a process of decision making.

Expert systems provide benefits such as improved decisions, reduced errors, reduced costs, reduced training time, and better quality and service. They have been used in applications for making decisions about granting credit and for diagnosing equipment problems, as well as in medical diagnostics, legal research, civil

TABLE 11.5

Major Types of AI Techniques

Expert systems	Represent the knowledge of experts as a set of rules that can be programmed so that a computer can assist human decision makers.
Machine learning	Software that can identify patterns in very large databases without explicit programming although with significant human training.
Neural networks and deep learning	Loosely based on human neurons, algorithms that can be trained to classify objects into known categories based on data inputs. Deep learning uses multiple layers of neural networks to reveal the underlying patterns in data, and in some limited cases identify patterns without human training.
Genetic algorithms	Algorithms based loosely on evolutionary natural selection and mutation, commonly used to generate high-quality solutions to optimization and search problems.
Natural language processing	Algorithms that make it possible for a computer to understand and analyze natural human language.
Computer vision systems	Systems that can view and extract information from real-world images.
Robotics	Use of machines that can substitute for human movements as well as computer systems for their control and information processing.
Intelligent agents	Software agents that use built-in or learned knowledge to perform specific tasks or services for an individual.

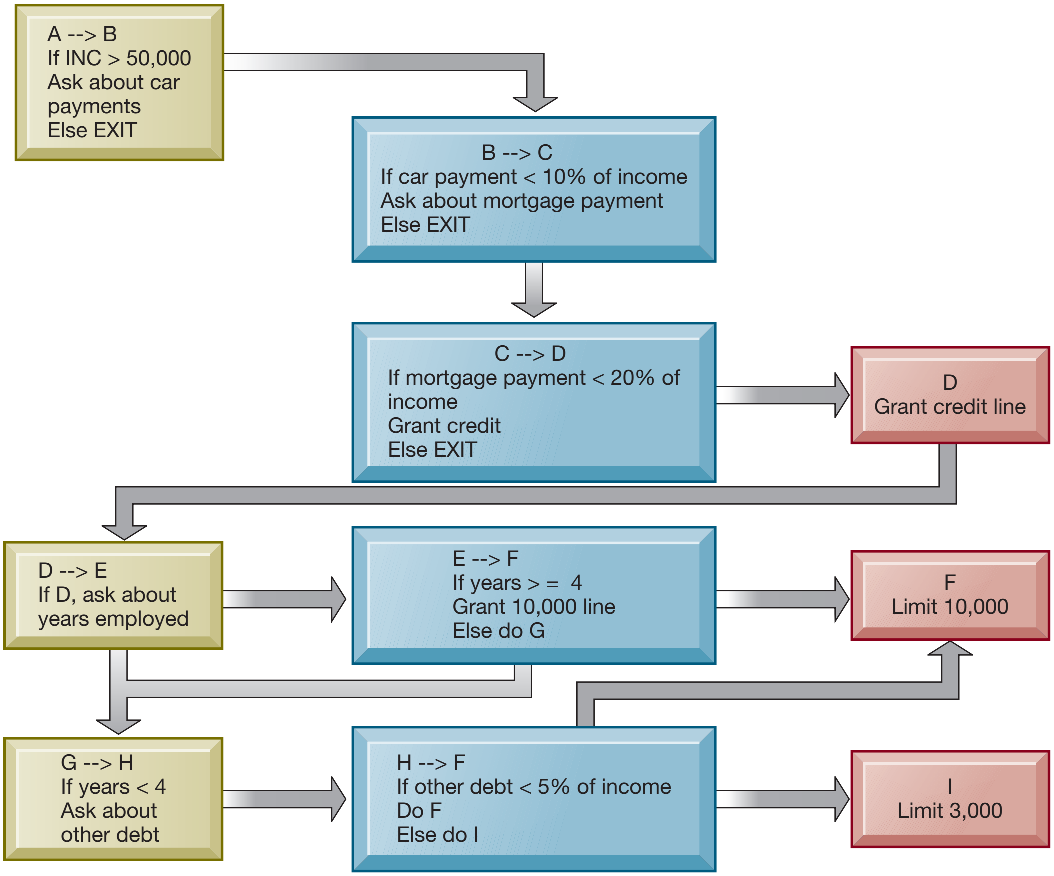


Figure 11.8
Rules in an Expert System.
An expert system contains a number of rules to be followed. The rules are interconnected, the number of outcomes is known in advance and is limited, there are multiple paths to the same outcome, and the system can consider multiple rules at a single time. The rules illustrated are for simple credit-granting expert systems.

engineering, building maintenance, drawing up building plans, and educational technology (personalized learning and responsive testing) (Maor, 2003). For instance, if you were the project manager of a 14-story office building and were given the task of configuring the building's air conditioning system, which has hundreds of parts and subassemblies, an expert system could walk you through the process by asking a series of questions, producing an order to suppliers, and providing an overall cost estimate for the project, all in a matter of hours rather than weeks. See Figure 11.8 for an expert system for credit granting.

How Expert Systems Work

Expert systems model human knowledge as a set of rules that collectively are called the **knowledge base**. Expert systems can have from a handful to many thousands of rules, depending on the complexity of the decision-making problem. The strategy used to search through the collection of rules and formulate conclusions is called the **inference engine**. The inference engine works by searching through the rules and firing those rules that are triggered by facts the user gathers and enters.

Expert systems have a number of limitations, the most important of which is that even experts can't explain how they make decisions: they know more than they can say. People drive cars, for instance, but are challenged to say how they do it. The knowledge base can become chaotic as the number of rules can reach into the thousands. In rapidly changing environments, say medical diagnosis, the rules change and need to be continually updated. Expert systems are not useful for dealing with unstructured problems that managers and employees typically encounter, and do not use real-time data to guide their decisions. Expert systems do not scale well to the kinds of very large data sets produced by the Internet and the Internet of Things (IoT), and they are expensive to build. For these reasons, expert system development has slowed in the last decade to small domains of expert knowledge such as automobile diagnosis.

MACHINE LEARNING

More than 75 percent of AI development today involves some kind of **machine learning (ML)** accomplished by neural networks, genetic algorithms, and deep learning networks, with the main focus on finding patterns in data, and classifying data inputs into known (and unknown) outputs. Machine learning is based on an entirely different AI paradigm than expert systems. In machine learning there are no experts, and there is no effort to write computer code for rules reflecting an expert's understanding. Instead, ML begins with very large data sets with tens to hundreds of millions of data points and finds patterns and relationships in the data by analyzing a large set of examples and making a statistical inference. Many of today's Big Data analytics applications such as Royal Dutch Shell's predictive maintenance system or Siemen's process mining system describd in this chapter utilize machine learning. Table 11.6 provides some examples of how leading business firms are using various types of machine learning.

Facebook has over 200 million monthly users in the United States who spend an average of 35 minutes on site daily. The firm displays an estimated 1 billion ads monthly to this audience, and it decides which ads to show each person in less than one second. For each person, Facebook bases this decision on the prior behavior of its users, including information shared (posts, comments, Likes), the activity of their social network friends, background information supplied to Facebook (age, gender, location, devices used), information supplied by advertisers (email address, prior purchases), and user activity on apps and other websites that Facebook can track. Facebook uses ML to identify patterns in the dataset, and to estimate the probability that any specific user will click on a particular ad based on the patterns of behavior they have identified. Analysts estimate that Facebook uses at least 100,000 servers located in several very large-scale "hyper datacenters" to perform this task. At the end of this process is a simple show ad/no show ad result.

The current response rate (click rate) to Facebook ads is about 0.1 percent, roughly four times that of an untargeted display ad although not as good as targeted email campaigns (about 3 percent), or Google Search ads (about 2 percent). All of the very large Internet consumer firms, including Amazon, Alphabet's Google, Microsoft, Alibaba, Tencent, Netflix, and Baidu, use similar ML algorithms. Obviously, no human or group of humans could achieve these results given the enormous database size, the speed of transactions, or the complexity of working in real time. The benefits of ML illustrated by this brief example come down to an extraordinary ability to recognize patterns at the scale of millions of people in a matter of seconds, and classify objects into discrete categories.

Supervised and Unsupervised Learning

Nearly all machine learning today involves **supervised learning**, in which the system is "trained" by providing specific examples of desired inputs and outputs identified by humans in advance. A very large database is developed, say 10 million photos posted

TABLE 11.6

Examples of Machine Learning

WellsFargo	Aiera system reads and analyzes a half-million documents daily for 1,600 stocks, and produces buy and sell calls for 550 stocks followed by their wealth management unit.
Netflix	Recommender system based on video similarity algorithm uses statistical and machine learning to develop a personalized selection of videos for each of its 150 million subscribers worldwide.
Schindler Group	Monitors over one million elevators and walkways using GE's Predix operating system and machine learning to make predictions about needed maintenance.
PayPal	Uses machine learning algorithms to identify patterns of fraud for 170 million customers who generate four billion transactions annually.

on the Internet, and then split into two sections, one a development database and the other a test database. Humans select a target, let's say to identify all photos that contain a car image. Humans feed a large collection of verified pictures, some of which contain a car image, into a neural network (described below) that proceeds iteratively through the development database in millions of cycles, until eventually the system can identify photos with a car at an acceptable rate. The machine learning system is then tested using the test database to ensure the algorithms can achieve the same results with a different set of photos. In many cases, but not all, machine learning can come close to or equal human efforts, but on a very much larger scale and much faster. Over time, with tweaking by programmers, and by making the database even bigger, using ever larger computing systems, the system will improve its performance, and in that sense, can learn. Supervised learning is one technique used to develop autonomous vehicles that need to be able to recognize objects around them, such as people, other cars, buildings, and lines on the pavement to guide them (see the chapter-ending case study).

In **unsupervised learning**, the same procedures are followed, but humans do not feed the system examples. Instead, the system is asked to process the development database and report whatever patterns it finds. For instance, in a seminal research effort often referred to "The Cat Paper," researchers collected 10 million YouTube photos from videos and built an ML system that could detect human faces without labeling or "teaching" the machine with verified human face photos (Le et al., 2011). Researchers developed a brute force neural network computer system composed of 1,000 machines with 16,000 core processors loaned by Google. The systems processors had a total of 1 billion connections to one another, creating a very large network that imitated on a small scale the neurons and synapses (connections) of a human brain. The result was a system that could detect human faces in photos, as well as cat faces and human bodies. The system was then tested on 22,000 object images on ImageNet (a large online visual database), and achieved a 16 percent accuracy rate. In principle then, it is possible to create machine learning systems that can "teach themselves" about the world without human intervention. But there's a long way to go: we wouldn't want to use autonomous cars that were guided by systems with a 16 percent accuracy rate! Nevertheless, this research was a 75 percent improvement over previous efforts.

To put this in perspective, a one-year-old human baby can recognize faces, cats, tables, doors, windows, and hundreds of other objects it has been exposed to, and continuously catalogs new experiences that it seeks out by itself for recognition in the future. But babies have a huge computational advantage over our biggest ML research systems. The human adult brain has an estimated 84 billion neurons, each with over 10,000 connections to other neurons (synapses), and over one trillion total connections in its network (brain). The human brain consumes about 7 watts of energy to operate. Modern *homo sapiens* have been programmed (by nature) for an estimated 300,000 years, and their mammalian predecessors for 2.5 million years. For these reasons, machine learning is applicable today in a limited number of situations where there are very large databases and computing facilities, most desired outcomes are already defined by humans, the output is binary (0,1), and there is a talented and large group of software and system engineers working the problem. A large power supply measuring up to several hundred thousand watts for large problems or continuous operations like Google or Facebook also is helpful.

NEURAL NETWORKS

A neural network is composed of interconnected units called neurons. Each neuron can take data from other neurons, and transfer data to other neurons in the system. The artificial neurons are not biological physical entities as in the human brain, but instead are software programs and mathematical models that perform the input and output function of neurons. The strength of the connections (weight) can be controlled by researchers using a Learning Rule, an algorithm that systematically alters the strength of the connections among the neurons to produce the final desired output that could be identifying a picture of a cancerous tumor, fraudulent credit card transactions, or suspicious telephone calling patterns.

Neural networks find patterns and relationships in very large amounts of data that would be too complicated and difficult for a human being to analyze by using machine learning algorithms and computational models that are loosely based on how the biological human brain is thought to operate. Neural networks are pattern detection programs. Neural networks learn patterns from large quantities of data by sifting through the data, and ultimately finding pathways through the network of thousands of neurons. Some pathways are more successful than others in their ability to identify objects like cars, animals, faces, and voices. There may be millions of pathways through the data. An algorithm (the Learning Rule mentioned above) identifies these successful paths, and strengthens the connection among neurons in these pathways. This process is repeated thousands or millions of times until only the most successful pathways are identified. The Learning Rule identifies the best or optimal pathways through the data. At some point, after millions of pathways are analyzed, the process stops when an acceptable level of pattern recognition is reached, for instance, successfully identifying cancerous tumors about as well as humans, or even better than humans.

Figure 11.9 represents one type of neural network comprising an input layer, a processing layer, and an output layer. Humans train the network by feeding it a set of outcomes they want the machine to learn. For instance, if the objective is to build a system that can identify patterns in fraudulent credit card purchases, the system is trained using actual examples of fraudulent transactions. The data set may be composed of a million examples of fraudulent transactions. The data set is divided into two segments: a training data set, and a test data set. The training data set is used to train the system. After millions of test runs, the program hopefully will identify the best path through the data. To verify the accuracy of the system, it is then used on the test data set, which the system has not analyzed before. If successful, the system will be tested on new data sets. The neural network in Figure 11.9 has learned how to identify a likely fraudulent credit card purchase.

Neural network applications in medicine, science, and business address problems in pattern classification, prediction probabilities, and control and optimization. In medicine, neural network applications are used for screening patients for coronary artery disease, for diagnosing epilepsy and Alzheimer's disease, and for performing pattern recognition of pathology images, including certain cancers. The financial industry uses neural networks to discern patterns in vast pools of data that might help investment firms predict the performance of equities, corporate bond ratings, or corporate bankruptcies. Visa International uses a neural network to help detect credit card fraud by monitoring all Visa transactions for sudden changes in the buying patterns of cardholders. Table 11.7 provides examples of neural networks.

Figure 11.9
How a Neural Network Works.
A neural network uses rules it "learns" from patterns in data to construct a hidden layer of logic. The hidden layer then processes inputs, classifying them based on the experience of the model. In this example, the neural network has been trained to distinguish between valid and fraudulent credit card purchases.

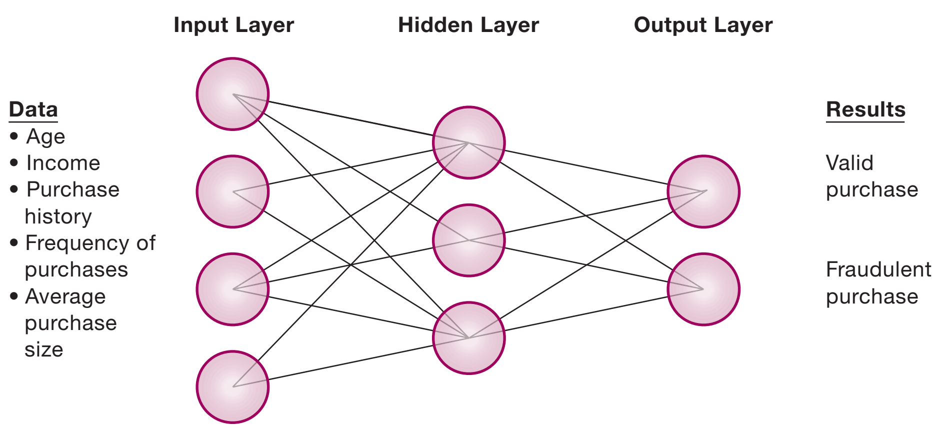


TABLE 11.7
Examples of Neural Networks

Functionality	Inputs	Process	Outputs/ Application
Computer vision	Millions of digital images, videos, or sensors	Recognize patterns in images, and objects	Photo tagging; facial recognition; autonomous vehicles
Speech recognition	Digital soundtracks, voices	Recognize patterns and meaning in soundtracks and speech	Digital assistants, chat-bots, help centers
Machine controls, diagnostics	Internet of Things: thousands of sensors	Identify operational status, patterns of failure	Preventive maintenance; quality control
Language translation	Millions of sentences in various languages	Identify patterns in multiple languages	Translate sentences from one language to another
Transaction analysis	Millions of loan applications, stock trades, phone calls	Identify patterns in financial and other transactions	Fraud control; theft of services; stock market predictions
Targeted online ads	Millions of browser histories	Identify clusters of consumers; preferences	Programmatic advertising

"Deep Learning" Neural Networks

"Deep learning" neural networks are more complex, with many layers of transformation of the input data to produce a target output. Collections of neurons are called nodes or layers. Deep learning networks are in their infancy. They are used almost exclusively for pattern detection on unlabeled data where the system is not told what to look for specifically but to simply discover patterns in the data. The system is expected to be self-taught. See Figure 11.10.

For instance, in our earlier example of unsupervised learning involving a machine learning system that could identify cats (The Cat Paper) and other objects without training, the system used was a deep learning network. It consisted of three layers of neural networks (layers 1, 2, and 3). Each of these layers has two levels of pattern detection (levels 1 and 2). Each level was developed to identify a low-level feature of the photos: layer 1 identified lines in the photos, and layer 2 identified circles. The result of the first layer may be blobs and fuzzy edges. Second and third layers refine the images emerging from the first layer, until at the end of the process the system can distinguish cats, dogs, and humans, although in this case not very well, with a 16 percent accuracy rate.

Many pundits believe deep learning networks come closer to the "Grand Vision" of AI where ML systems would be capable of learning like a human being. Others who work in ML and deep learning are more critical (Marcus, 2018; Pearl 2016).

Limitations of Neural Networks and Machine Learning

Neural networks have a number of limitations currently. They require very large data sets to identify patterns. There are often many patterns in large data sets that are nonsensical, and it takes humans to choose which patterns "make sense." Many patterns in large data sets are ephemeral: there may be a pattern in the stock market, or the performance of professional sports teams, but they do not last long. In many important decision situations there are no large data sets. For instance, should you

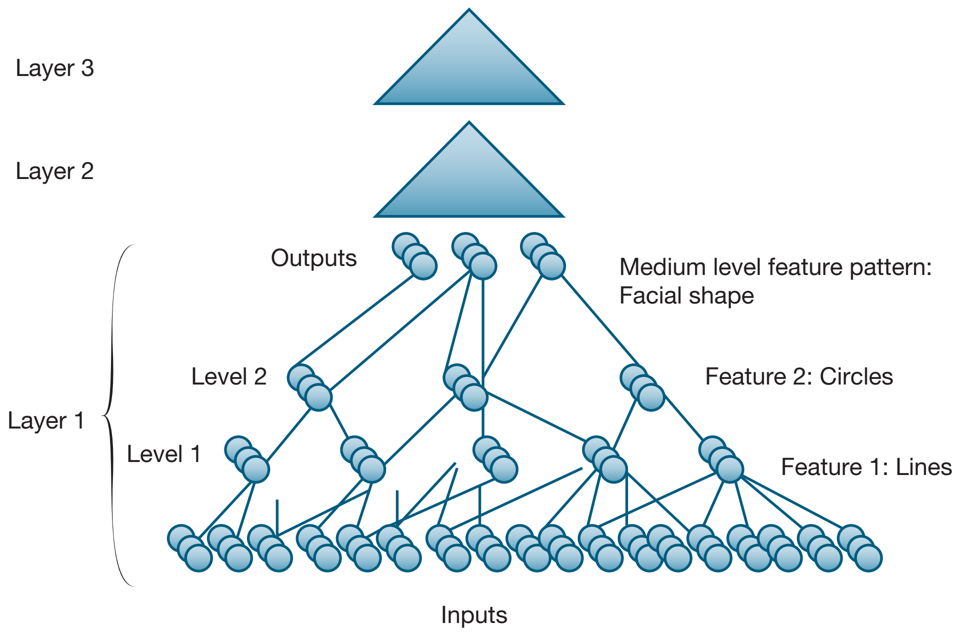


Figure 11.10
A Deep Learning Network.
Deep learning networks consist of many layers of neural networks working in a hierarchical fashion to detect patterns. Shown here is an expanded look at layer 1. Other layers have the same structure.

apply to College A or College B? Should we merge with another company? Answers to many important questions are difficult to specify, or describe, and in that sense are only semistructured at best, and depend greatly on human assessments, judgments, and sentiments.

Systems engineers do not know why neural networks and machine learning arrive at conclusions (Olah and Satyanarayan, 2018). For instance, in the case of the IBM Watson computer playing Jeopardy, researchers could not say exactly why Watson chose the answers it did, only that they were either right or wrong. Most real-world ML applications in business involve classifying digital objects into simple binary categories (yes or no; 0 or 1). But many of the significant problems facing managers, firms, and organizations do not have binary solutions. Neural networks may not perform well if their training covers too little or too much data. AI systems have no sense of ethics: they may recommend actions that are illegal or immoral. In most current applications, AI systems are best used as tools for relatively low-level decisions in systems where errors do not have catastrophic consequences like death or injury, aiding but not substituting for managers.

GENETIC ALGORITHMS

Genetic algorithms are another form of machine learning. Genetic algorithms are useful for finding the optimal solution for a specific problem by examining a very large number of alternative solutions for that problem. Their method of solving problems is based on ideas inspired by evolutionary biology such as inheritance, mutation, selection, and crossover (recombination).

A genetic algorithm works by searching a population of randomly generated strings of binary digits to identify the right string representing the best possible solution for the problem. As solutions alter and combine, the worst ones are discarded and the better ones survive to go on to produce even better solutions.

In Figure 11.11, each string corresponds to one of the variables in the problem. One applies a test for fitness, ranking the strings in the population according to their level of desirability as possible solutions. After the initial population is evaluated for fitness, the algorithm then produces the next generation of strings, consisting of strings that survived the fitness test plus offspring strings produced from mating pairs of strings, and tests their fitness. The process continues until a solution is reached.

		Length	Width	Weight	Fitness
1 1 0 1 1 0	1	Long	Wide	Light	55
1 0 1 0 0 0	2	Short	Narrow	Heavy	49
0 0 0 1 0 1	3	Long	Narrow	Heavy	36
1 0 1 1 0 1	4	Short	Medium	Light	61
0 1 0 1 0 1	5	Long	Medium	Very light	74

A population of chromosomes **Decoding of chromosomes** **Evaluation of chromosomes**

Figure 11.11
The Components of a Genetic Algorithm.
This example illustrates an initial population of "chromosomes," each representing a different solution. The genetic algorithm uses an iterative process to refine the initial solutions so that the better ones, those with the higher fitness, are more likely to emerge as the best solution.

Genetic algorithms are used to solve problems that are dynamic and complex, involving hundreds or thousands of variables or formulas. The problem must be one whose range of possible solutions can be represented genetically and for which criteria can be established for evaluating fitness. Genetic algorithms expedite the solution because they can evaluate many solution alternatives quickly to find the best one. For example, General Electric engineers used genetic algorithms to help optimize the design for jet turbine aircraft engines, in which each design change required changes in up to 100 variables. The supply chain management software from JDA software uses genetic algorithms to optimize production-scheduling models, incorporating hundreds of thousands of details about customer orders, material and resource availability, manufacturing and distribution capability, and delivery dates.

NATURAL LANGUAGE PROCESSING, COMPUTER VISION SYSTEMS, AND ROBOTICS

Other important AI techniques include natural language processing, computer vision systems, and robotics.

Natural Language Processing

Human language is not always precise. It is often ambiguous, and meanings of words can depend on complex variables such as slang, regional dialects, and social context. **Natural language processing (NLP)** makes it possible for a computer to analyze natural language—language that human beings instinctively use, not language specially formatted to be understood by computers. NLP algorithms are typically based on machine learning, including deep learning, which can learn how to identify a speaker's intent from many examples. Akershus University Hospital, described in the chapter-opening case, used NLP and IBM Watson Explorer to sift through thousands of medical records with unstructured textual data expressed in everyday language like natural speech. The algorithms could read text on a medical record and classify its meaning. You can also see natural language processing at work in leading search engines such as Google, spam filtering systems, and text mining sentiment analysis (discussed in Chapter 6).

Tokyo-based Mizuho Bank employs advanced speech recognition technology, IBM® Watson™ content analytics software, and a cloud services infrastructure to improve contact center agents' interactions with customers. After converting the customer's speech to textual data, the solution applies natural language processing algorithms based on machine learning analysis of interactions with thousands of customers. The system learns more and more from each customer interaction so that it can eventually infer the customer's specific needs or goals at each point of the conversation. It then formulates the optimal response, which is delivered in real time as a prompt on the agent's screen. By helping contact center agents more efficiently sense and respond to customer needs, this solution reduced the average duration of customer interactions by more than 6 percent (IBM, 2019).

Computer Vision Systems

Computer vision systems deal with how computers can emulate the human visual system to view and extract information from real-world images. Such systems incorporate image processing, pattern recognition, and image understanding. An example is Facebook's facial recognition tool called DeepFace, which is nearly as accurate as the human brain in recognizing a face. DeepFace will help Facebook improve the accuracy of Facebook's existing facial recognition capabilities to ensure that every photo of a Facebook user is connected to that person's Facebook account. Computer vision systems are also used in autonomous vehicles such as drones and self-driving cars (see the chapter-ending case), industrial machine vision systems (e.g., inspecting bottles), military applications, and robotic tools.

In 2017, the National Basketball Association (NBA) decided to allow sponsors to place small logo patches representing their brands on player uniforms. This advertising investment turned out to be worth its multimillion-dollar cost. According to GumGum, an AI company focusing on computer vision technology, the image placed by The Goodyear Tire & Rubber Co. on the uniforms of the Cleveland Cavaliers generated $3.4 million in value from social media exposure alone during the first half of the baseball season. GumGum develops algorithms that enable computers to identify what's happening in imagery. GumGum used computer vision technology to thoroughly analyze broadcast and social media content for placement, exposure, and duration involving Goodyear images that appeared in online or in TV-generated NBA content. Instead of humans trying to monitor the number of times a logo appeared on a screen, GumGum's vision technology tracks and reports the data (Albertson, 2018).

Robotics

Robotics deals with the design, construction, operation, and use of movable machines that can substitute for humans along with computer systems for their control, sensory feedback, and information processing. Robots cannot substitute entirely for people but are programmed to perform a specific series of actions automatically. They are often are used in dangerous environments (such as bomb detection and deactivation), manufacturing processes, military operations (drones), and medical procedures (surgical robots). Many employees now worry whether robots will replace people entirely and take away their jobs.

The most widespread use of robotic technology has been in manufacturing. For example, automobile assembly lines employ robots to do heavy lifting, welding, applying glue, and painting. People still do most of the final assembly of cars, especially when installing small parts or wiring that needs to be guided into place. A Renault SA plant in Cleon, France, now uses robots from Universal Robots AS of Denmark to drive screws into engines, especially those that go into places people find hard to access. The robots verify that parts are properly fastened and check to make sure the correct part is being used. The Renault robots are also capable of working in proximity to people and slowing down or stopping to avoid hurting them.

INTELLIGENT AGENTS

Intelligent agents are software programs that work in the background without direct human intervention to carry out specific tasks for an individual user, business process, or software application. The agent uses a limited built-in or learned knowledge base to accomplish tasks or make decisions on the user's behalf, such as deleting junk email, scheduling appointments, or finding the cheapest airfare to California.

There are many intelligent agent applications today in operating systems, application software, email systems, mobile computing software, and network tools. Of special interest to business are intelligent agent bots that search for information on the Internet. Chapter 7 describes how shopping bots help consumers find products they want and assist them in comparing prices and other features.

Although some software agents are programmed to follow a simple set of rules, others are capable of learning from experience and adjusting their behavior using machine learning and natural language processing. Siri, a virtual assistant application on Apple's iPhone and iPad, is an example. Siri uses natural language processing to answer questions, make recommendations, and perform actions. The software adapts to the user's individual preferences over time and personalizes results, performing tasks such as getting directions, scheduling appointments, and sending messages. Similar products include Google Now, Microsoft's Cortana, and Amazon's Alexa.

Chatbots (chatterbots) are software agents designed to simulate a conversation with one or more human users via textual or auditory methods. They try to understand what you type or say and respond by answering questions or executing tasks. They provide automated conversations that allow users to do things like check the weather, manage personal finances, shop online, and receive help when they have questions for customer service. Vodafone, a multinational telecommunications company, uses a chatbot to answer 80,000 questions per month, reducing contact center calls for 75 percent of the customers it chats with. Vodafone staff use the chatbot to access accurate, up-to-date information on Vodafone products and services. Facebook has integrated chatbots into its Messenger messaging app so that an outside company with a Facebook brand page can interact with Facebook users through the chat program. Today's chatbots perform very basic functions. As they become more technologically advanced, people using IT applications will increasingly use these "conversational agents" as a major tool for interacting with systems.

11-5 How will MIS help my career?

Here is how Chapter 11 and this book will help you find an entry-level job as a sales assistant for an AI company.

THE COMPANY

RMD Technology, an artificial intelligence company based in Stockholm, is looking for an entry-level sales assistant. RMD specializes in computer vision technology, seeking to unlock the value of visual content produced daily across diverse data sets to solve problems for a variety of industries, including advertising and professional sports.

POSITION DESCRIPTION

The sales assistant will work closely with the sales team on planning and staging events, database management, administrative tasks, and account research to support sales and marketing objectives. Job responsibilities include:

- Using Salesforce.com for lead generation collection, data entry, and maintenance.
- Using Excel to update sales team resources.

- Scheduling meetings and taking meeting notes.
- Assisting with research on sales accounts and new event ideas and locations.
- Assisting sales with client meeting preparation.
- Assembling promotional materials.

JOB REQUIREMENTS

- Recent college graduate.
- Bachelor's degree in marketing, MIS, finance, or liberal arts.
- Strong interest in learning the business and industry.
- Knowledge of Microsoft Office essential.
- Attention to detail, effective communication skills, enthusiastic attitude, and the ability to thrive in a fast-paced environment.

INTERVIEW QUESTIONS

- What do you know about our company and about computer vision systems? Have you ever done any work with AI technology?
- Have you ever worked with Salesforce.com? How have you used the software?
- What is your proficiency level with Microsoft Office tools? What work have you done with Excel spreadsheets?
- Can you provide samples of your writing to demonstrate your communication skills and sense of detail?

AUTHOR TIPS

- Review the section of this chapter on AI and use the web to find out more about computer vision systems.
- Use the web and LinkedIn to find out more about this company—its products, services, and competitors and the way it operates. Think about what it needs to support its sales team and how you could specifically contribute.
- Learn what you can about Salesforce.com, with attention to how it handles lead generation, data entry, and maintenance.
- Inquire exactly how you would be using Excel in this job. Describe some of the Excel work you have done and perhaps bring samples with you to the interview.

Review Summary

11-1 **What are the different types of decisions, and how does the decision-making process work?** Decisions may be structured, semistructured, or unstructured, with structured decisions clustering at the operational level of the organization and unstructured decisions at the strategic level. Decision making can be performed by individuals or groups and includes employees as well as operational, middle, and senior managers. There are four stages in decision making: intelligence, design, choice, and implementation.

11-2 **How do business intelligence and business analytics support decision making?** Business intelligence and analytics promise to deliver correct, nearly real-time information to decision makers, and the analytic tools help them quickly understand the information and take action. A business intelligence environment consists of data from the business environment, the BI infrastructure, a BA toolset, managerial users and methods, a BI delivery platform (MIS, DSS, or ESS), and the user interface. There are six analytic functionalities that BI systems deliver to achieve these ends: predefined production reports, parameterized reports, dashboards and scorecards, ad hoc queries and searches, the ability to drill down to detailed views of data, and the ability to model scenarios and create forecasts. BI analytics are starting to handle big data. Predictive analytics, location analytics, and operational intelligence are important analytic capabilities.

Management information systems (MIS) producing prepackaged production reports are typically used to support operational and middle management, whose decision making is fairly structured. For making unstructured decisions, analysts and super users employ decision-support systems (DSS) with powerful analytics and modeling tools, including spreadsheets and pivot tables. Senior executives making unstructured decisions use dashboards and visual interfaces displaying key performance information affecting the overall profitability, success, and strategy of the firm. The balanced scorecard and business performance management are two methodologies used in designing executive support systems (ESS).

11-3 **What is artificial intelligence (AI)? How does it differ from human intelligence?** The most ambitious vision of AI involves the attempt to build computer systems that try to think and act like humans. At present, artificial intelligence lacks the flexibility, breadth, and generality of human intelligence, but it can be used to capture, codify, and extend organizational knowledge in limited domains. AI systems today can perform many tasks that would be impossible for humans to accomplish, and can equal or come close to humans in certain well-defined tasks.

11-4 **What are the major types of AI techniques and how do they benefit organizations?** Expert systems capture tacit knowledge from a limited domain of human expertise and express that knowledge in the form of rules. Machine learning software can learn from previous data and examples. It can identify patterns in very large databases without explicit programming, although with significant human training

Neural networks consist of hardware and software that attempt to mimic the thought processes of the human brain. Neural networks are notable for their ability to learn on their own with some training, and to recognize patterns that cannot be easily identified by humans. Deep learning neural networks use multiple layers of neural networks to reveal the underlying patterns in data, and in some limited cases identify patterns without human training.

Genetic algorithms develop solutions to particular problems using genetically based processes such as fitness, crossover, and mutation. Genetic algorithms are useful for solving problems involving optimization where many alternatives or variables must be evaluated to generate an optimal solution.

Intelligent agents are software programs with built-in or learned knowledge bases that carry out specific tasks for an individual user, business process, or software application. Intelligent agents can be programmed to navigate through large amounts of data to locate useful information and in some cases act on that information on behalf of the user. Chatbots are software agents designed to simulate a conversation with one or more human users via textual or auditory methods.

Natural language processing technology makes it possible for a machine to understand human language and to process that information. Computer vision systems deal with how computers can emulate the human visual system to view and extract information from real-world images. Robotics deals with the design, construction, operation, and use of movable machines that can substitute for some human actions.

Key Terms

Artificial intelligence (AI), 429
Augmented reality (AR), 420
Balanced scorecard method, 428
Business performance management (BPM), 428
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Review Questions

11-1 What are the different types of decisions, and how does the decision-making process work?
- List and describe the different decision-making levels and groups in organizations and their decision-making requirements.
- Distinguish among an unstructured, semistructured, and structured decision.
- List and describe the stages in decision making.

11-2 How do business intelligence and business analytics support decision making?
- Define and describe business intelligence infrastructure and analytics toolsets.
- Describe ways that user interfaces make business analytics software suites more usable.
- Explain the purpose of a parameterized report.
- Describe how virtual reality and augmented reality enhance data visualization and decision making.
- Describe how a decision maker might be able to use geographic information systems.
- Describe a pivot table and suggest who might use it.
- Explain why predictive analytics are incorporated into BI applications.

11-3 What is artificial intelligence (AI)? How does it differ from human intelligence?
- Define artificial intelligence (AI).
- Explain how AI differs from human intelligence.

11-4 What are the major types of AI techniques and how do they benefit organizations?
- Define an expert system, describe how it works, and explain its value to business.
- Define machine learning, explain how it works, and give some examples of the kinds of problems it can solve.
- Compare supervised and unsupervised learning
- Define neural networks and deep learning neural networks, describing how they work and how they benefit organizations.
- Define and describe genetic algorithms, and intelligent agents. Explain how each works and the kinds of problems for which each is suited.
- Define and describe computer vision systems, natural language processing systems, and robotics and give examples of their applications in organizations.

Discussion Questions

11-5 If businesses used DSS and ESS more widely, would they make better decisions? Why or why not?
MyLab MIS

11-6 How much can business intelligence and business analytics help companies refine their business strategy? Explain your answer.
MyLab MIS

11-7 How intelligent are AI techniques? Explain your answer.
MyLab MIS

Hands-On MIS Projects

The projects in this section give you hands-on experience identifying opportunities for business intelligence, using a spreadsheet pivot table to analyze sales data, and using intelligent agents to research products for sale on the web. Visit **MyLab MIS** to access this chapter's Hands-On MIS Projects.

MANAGEMENT DECISION PROBLEMS

11-8 Dealerships for Toyota and other automobile manufacturers keep records of the mileage of cars they sell and service. Mileage data are used to remind customers of when they need to schedule service appointments, but they are used for other purposes as well. What kinds of decisions does this piece of data support at the local level and at the corporate level? What would happen if this piece of data were erroneous, for example, showing a mileage of 130,000 instead of 30,000? How would it affect decision making? Assess its business impact.

11-9 Applebee's is the largest casual dining chain in the world, with more than 1,800 locations throughout the United States and 20 other countries. The menu features beef, chicken, and pork items as well as burgers, pasta, and seafood. Applebee's CEO wants to make the restaurant more profitable by developing menus that are tastier and contain more items that customers want and are willing to pay for despite rising costs for gasoline and agricultural products. How might business intelligence help management implement this strategy? What pieces of data would Applebee's need to collect? What kinds of reports would be useful to help management make decisions about how to improve menus and profitability?

IMPROVING DECISION MAKING: USING PIVOT TABLES TO ANALYZE SALES DATA

Software skills: Pivot tables
Business skills: Analyzing sales data

11-10 This project gives you an opportunity to learn how to use Excel's PivotTable functionality to analyze a database or data list. Use the data file for Online Management Training Inc. described earlier in the chapter. This is a list of the sales transactions at OMT for one day. You can find this spreadsheet file at MyLab MIS. Use Excel's PivotTable to help you answer the following questions:

- Where are the average purchases higher? The answer might tell managers where to focus marketing and sales resources or pitch different messages to different regions.
- What form of payment is the most common? The answer could be used to emphasize in advertising the most preferred means of payment.
- Are there any times of day when purchases are most common? Do people buy products while at work (likely during the day) or at home (likely in the evening)?

- What's the relationship among region, type of product purchased, and average sales price?
- We provide instructions on how to use Excel PivotTables in our Learning Tracks.

IMPROVING DECISION MAKING: USING INTELLIGENT AGENTS FOR COMPARISON SHOPPING

Software skills: Web browser and shopping bot software
Business skills: Product evaluation and selection

11-11 This project will give you experience using shopping bots to search online for products, find product information, and find the best prices and vendors. Select a digital camera you might want to purchase, such as the Canon PowerShot SX530 or the Olympus Tough TG-5. Visit MySimon, BizRate.com, and Google Shopping to do price comparisons for you. Evaluate these shopping sites in terms of their ease of use, number of offerings, speed in obtaining information, thoroughness of information offered about the product and seller, and price selection. Which site or sites would you use and why? Which camera would you select and why? How helpful were these sites in making your decision?

COLLABORATION AND TEAMWORK PROJECT

Investigating Data-Driven Analytics in Sports

11-12 With three or four of your classmates, select a sport, such as football, baseball, basketball, or soccer. Use the web to research how the sport uses data and analytics to improve team performance or increase ticket sales to events. If possible, use Google Docs and Google Drive or Google Sites to brainstorm, organize, and develop a presentation of your findings for the class.

BUSINESS PROBLEM-SOLVING CASE

CAN CARS DRIVE THEMSELVES—AND SHOULD THEY?

Will cars really be able to drive themselves without human operators? Should they? And are they good business investments? Everyone is searching for answers.

Autonomous vehicle technology has reached a point where no automaker can ignore it. Every major auto maker is racing to develop and perfect autonomous vehicles, believing that the market for them could one day reach trillions of dollars. Companies such as Ford, General Motors, Nissan, Mercedes, Tesla, and others have invested billions in autonomous technology research and development. GM bought a self-driving car startup called Cruise. Ride-hailing companies like Uber and Lyft believe driverless cars that eliminate labor costs are key to their long-term profitability. (A study conducted by UBS shows that the cost per mile of a self-driving "robo-taxi" will be about 80 percent less than that of a traditional taxi.) Cars that drive themselves have been on the road in select locations in California, Arizona, Michigan, Paris, London, Singapore, and Beijing. Marketing firm ABI predicts that roughly 8 million vehicles with some level of self-driving capabilities will be shipped in 2025. In December 2018, Waymo, a subsidiary of Google Alphabet, launched a commercial self-driving taxi service called "Waymo One" in the Phoenix metropolitan area. A car that is supposed to take over driving from a human requires a powerful computer system that must process and analyze large amounts of data generated by myriad sensors, cameras, and other devices to control and adjust steering, accelerating, and braking in response to real-time conditions. Key technologies include the following:

Sensors: Self-driving cars are loaded with sensors of many different types. Sensors on car wheels measure the car's velocity as it drives and moves through traffic. Ultrasonic sensors measure and track positions of line curbs, sidewalks, and objects close to the car.

Cameras: Cameras are needed for spotting things like lane lines on the highway, speed signs, and traffic lights. Windshield-mounted cameras create a 3-D image of the road ahead. Cameras behind the rear-view mirror focus on lane markings. Infrared cameras pick up infrared beams emitted from headlamps to extend vision for night driving.

Lidars: Lidars are light detection and ranging devices that sit on top of most self-driving cars. A lidar fires out millions of laser beams every second, measuring how long they take to bounce back. The lidar takes in a 360-degree view of a car's surroundings, identifying nearby objects with an accuracy up to 2 centimeters. Lidars are very expensive and not yet robust enough for a life of potholes, extreme temperatures, rain, or snow.

GPS: A global positioning system (GPS) pinpoints the car's macro location, and is accurate to within 1.9 meters. Combined with reading from tachometers, gyroscopes, and altimeters, it provides initial positioning.

Radar: Radar bounces radio waves off objects to help see a car's surroundings, including blind spots, and is especially helpful for spotting big metallic objects, such as other vehicles.

Computer: All the data generated by these technologies needs to be combined, analyzed, and turned into a robot-friendly picture of the world, with instructions on how to move through it, requiring almost supercomputer-like processing power. Its software features obstacle avoidance algorithms, predictive modeling, and "smart" object discrimination (for example, knowing the difference between a bicycle and a motorcycle) to help the vehicle follow traffic rules and navigate obstacles.

Machine Learning, Deep Learning, and Computer Vision Technology: The car's computer system has to be "trained" using machine intelligence and deep learning to do things like detect lane lines and identify cyclists, by showing it millions of examples of the subject at hand. Because the world is too complex to write a rule for every possible scenario, cars must be able to "learn" from experience and figure out how to navigate on their own.

Maps: Before an autonomous car takes to the streets, its developers use cameras and lidars to map its territory in extreme detail. That information helps the car verify its sensor readings, and it is key for any vehicle to know its own location.

Self-driving car companies are notorious for overhyping their progress. Should we believe them? At this point, the outlook for them is clouded.

In March 2018, a self-driving Uber Volvo XC90 operating in autonomous mode struck and killed a woman in Tempe, Arizona. Uber suspended autonomous vehicle testing for a period of time. Even before the accident, Uber's self-driving cars were having trouble driving through construction zones and next to tall vehicles like big truck rigs. Uber's drivers had to intervene far more frequently than drivers in other autonomous car projects.

The Uber accident raised questions about whether autonomous vehicles were even ready to be tested on public roads and how regulators should deal with this. Autonomous vehicle technology's defenders pointed out that nearly 40,000 people die on US roads every year, and human error causes more than 90 percent of crashes. But no matter how quickly self-driving proliferates, it will be a long time before the robots can put a serious dent in those numbers and convince everyday folks that they're better off letting the cars do the driving.

While proponents of self-driving cars like Tesla's Elon Musk envision a self-driving world where almost all traffic accidents would be eliminated, and the elderly and disabled could travel freely, most Americans think otherwise. A Pew Research Center survey found that most people did not want to ride in self-driving cars and were unsure if they would make roads more dangerous or safer. Eighty-seven percent wanted a person always behind the wheel, ready to take over if something went wrong.

There's still plenty that needs to be improved before self-driving vehicles could safely take to the road. Autonomous vehicles are not yet able to operate safely in all weather conditions. Heavy rain or snow can confuse current car radar and lidar systems—autonomous vehicles can't operate on their own in such weather conditions. These vehicles also have trouble when tree branches hang too low or bridges and roads have faint lane markings. On some roads, self-driving vehicles will have to make guidance decisions without the benefit of white lines or clear demarcations at the edge of the road, including Botts' Dots (small plastic markers that define lanes). Botts' Dots are not believed to be effective lane-marking for autonomous vehicles.

Computer vision systems are able to reliably recognize objects. What remains challenging is "scene understanding"—for example, the ability to determine whether a bag on the road is empty or is hiding bricks or heavy objects inside. Although autonomous vehicle vision systems are now capable of picking out traffic lights reliably, they are not always able to make correct decisions if traffic lights are not working. This requires experience, intuition, and knowing how to cooperate among multiple vehicles. Autonomous vehicles must also be able to recognize a person moving alongside a road, determine whether that person is riding a bicycle, and predict how that person is likely to respond and behave. All of that is still difficult for an autonomous vehicle to do right now. Chaotic environments such as congested streets teeming with cars, pedestrians, and cyclists are especially difficult for self-driving cars to navigate.

Driving a car to merge into rapidly flowing lanes of traffic is an intricate task that often requires eye contact with oncoming drivers. How can autonomous vehicles communicate with humans and other machines to let them know what they want to do? Researchers are investigating whether electronic signs and car-to-car communication systems would solve this problem. There's also what's called the "trolley problem": In a situation where a crash is unavoidable, how does a robot car decide whom or what to hit? Should it hit the car coming up on its left or a tree on the side of the road?

Less advanced versions of autonomous vehicle technology are already on the market. Cadillac Super Cruise, Nissan ProPILOT Assist, and Tesla Autopilot are capable of keeping a car in its lane and a safe distance from other cars, allowing the "driver" behind the wheel to take hands off the wheel, provided that person keeps paying attention and is ready to take control if needed. These less-advanced systems can't see things like stopped fire trucks or traffic lights. But humans haven't made good driving backups because their attention tends to wander. At least two Tesla drivers in the United States have died using the system. (One hit a truck in 2016, another hit a highway barrier in 2018.) There is what is called a "hand-off problem." A semiautonomous car needs to be able to determine what its human "driver" is doing and how to get that person to take the wheel when needed.

And let's not forget security. A self-driving car is essentially a collection of networked computers and sensors linked wirelessly to the outside world, and it is no more secure than other networked systems. Keeping systems safe from intruders who want to crash or weaponize cars may prove to be the greatest challenge confronting autonomous vehicles in the future.

A computer-driven car that can handle any situation as well as a human under all conditions is decades away at best. Researchers at Cleveland State University estimate that only 10 to 30 percent of all vehicles will be fully self-driving by 2030. PwC analysts estimate that 12 percent of all vehicles will be fully autonomous by then, but they will only work in geographically constrined areas under good weather conditions, as does Waymo's fleet of sef-driving vans in Phoenix. Truly autonomous cars are still science fiction.

What is more likely is that self-driving technology will be incorporated into human-driven cars, Current auto models are being equipped with technologies such as advanced object recognition, radar-and-laser detection, some capability to take control of driving if the driver has made a mistake, and ultradetailed highway maps that were originally developed for self-driving vehicles. By 2022 nearly all new vehicles in the United States will have automatic emergency braking, which reduces rear-end crashes by 50 percent and crashes with injuries by 56 percent. Once emergency braking technology has been fully deployed, it could reduce fatalities and injuries from rear-end crashes by 80 percent. Human-driven vehicles with some level of self-driving technology will become safer at a rate that completely autonomous vehicles may have trouble matching. This makes the need for fully self-driving cars less compelling.

Many analysts expect the first deployment of self-driving technology will be robot taxi services operating in limited conditions and areas, so their operators can avoid particularly tricky intersections and make sure everything is mapped in fine detail. The Boston Consulting Group predicts that 25 percent of all miles driven in the United States by 2030 may be by shared self-driving vehicles. To take a ride, you'd probably have to use predetermined pickup and drop-off points, so your car can always pull over safely and legally. The makers of self-driving cars will be figuring out how much to charge so they can recoup their research and development costs, but not so much as to dissuade potential riders. They'll struggle with regulators and insurance companies over what to do in the inevitable event of a crash.

The accidents that self-driving cars have experienced so far point to the need to create a dependable standard for measuring reliability and safety. By 2018, 29 states had enacted legislation regulating autonomous vehicles, with a few states requiring a safety driver always be in the car ready to take control. US federal regulators have delayed formulating an overarching set of self-driving car standards, leaving a gap for the states to fill. The federal government is still working on autonomous vehicle legislation. H.R. 3388, a bill passed by voice vote last year, would help create uniform standards for the development of driverless cars.

Sources: Christopher Mims, "Self-Driving Cars Have a Problem: Safer Human-Driven Ones," *Wall Street Journal*, June 15, 2019, and "Driverless Hype Collides with Merciless Reality," *Wall Street Journal*, September 13, 2018; National Conference of State Legislatures, "Autonomous Vehicles—Self Driving Vehicles Enacted Legislation," www.ncsl.org, accessed June 25, 2019; Matt McCall, "Why Autonomous Vehicles Are Such a Game-Changer for Uber and Lyft," InvestorPlace.com, March 25, 2019; Brent Kenwell, "This Is How Many Autonomous Cars Will Be on the Road in 2025," TheStreet.com, April 23, 2018; Jack Karsten and Darrell West, "The State of Self-Driving Car Laws Across the U.S.," Brookings Institute, May 1, 2018; Alex Davies, "The WIRED Guide to Self-Driving Cars," *WIRED*, May 17, 2018; Daisuke Wakabashai, "Uber's Self-Driving Cars Were Struggling Before Arizona Crash," *New York Times*, March 23, 2018; Kevin Roose, "The Self-Driving Car Industry's Biggest Turning Point Yet," *New York Times*, March 29, 2018; Tim Higgins, "VW, Hyundai Turn to Driverless-Car Startup in Silicon Valley," *Wall Street Journal*, January 4, 2018; John Markoff, "A Guide to Challenges Facing Self-Driving Car Technologists," *New York Times*, June 7, 2017; and The Editorial Board, "Would You Buy a Self-Driving Future from These Guys?" *New York Times*, October 14, 2017.

CASE STUDY QUESTIONS

11-13 What are the people, organizational, and technology challenges posed by self-driving car technology?

11-14 Are self-driving cars good business investments? Explain your answer.

11-15 What ethical and social issues are raised by self-driving car technology?

11-16 Will cars really be able to drive themselves without human operators? Should they?

Chapter 11 References

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