As a day shift nurse on a patient-care unit, you perform assessments on your patients at the beginning of the shift. The first patient that you assess is an 85-year-old man admitted yesterday with pneumonia. During shift report, the night nurse stated the patient had a fever on admission but that the patient’s temperature was normal during the night shift. The patient had an elevated white blood cell count of 12.4 K/cmm on admission and received three doses of IV antibiotics since admission. As you assess the patient’s vital signs, you find the patient has a temperature of 101.1°F (38.4°C). The patient offered no complaints other than shortness of breath. You noted the patient is flushed with a respiratory rate of 20 and a pulse oximeter reading of 95% on 1.5L of oxygen delivered through a nasal cannula. His repeat white blood cell count on the morning of your care is 13.2 K/cmm. Prior to your assessment, the healthcare team enters the patient’s room. The physician asks, “Is he improving?”

•*How will you respond to the physician?*

•*What questions should you have asked during the handoff shift report when it was reported that the patient had a normal temperature during the night shift?*

•*Is a temperature finding of 101.1°F or a white blood cell count of 13.2 K/cmm an improvement?*

Quality is whatever patients and family members define it to be. Beyond the prevention, reduction, or elimination of harm is the search for innovations and breakthrough improvements that contribute to quality outcomes. With innovative improvements come the opportunity to advance good performance to excellence in performance. Such innovations occur with visionary thinking of what can be, what healthcare processes can be changed to enhance patient and staff satisfaction, and by understanding and applying quality improvement (QI) methods into our daily clinical practice. This chapter focuses on the science and process of QI.

For nurses to obtain the necessary knowledge, skills, and attitudes to continuously improve healthcare quality, safety, and systems used to delivery healthcare, the Quality and Safety Education for Nurses project ([QSEN Institute, 2017](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml?favre=brett#ref10); [www.qsen.org](http://www.qsen.org/),) defines **QI** as to “Use data to monitor the outcomes of care processes and use improvement methods to design and test changes to continuously improve the quality and safety of health care systems.”

This chapter includes defining data and commonly used descriptive statistics applied in QI activities. We explore the types and uses of data for QI including how data are displayed for analysis and how data are analyzed to identify both the need for improvement or if improvement occurred. Statistical process control (SPC) is introduced to include the run and **control charts**. When indicated, interprofessional teams may conduct QI activities. The teams have a variety of improvement tools and methods they can employ. The most basic and effective processes used by teams are described.

**WHAT ARE DATA**

Nursing practice decisions and organizational healthcare processes all produce outcome data that can be measured, displayed, and compared. So what are data? **Data** are the raw numbers or results collected to measure processes and outcomes. Data can also be results provided by external sources, such as the number of acute-care Joint Commission survey findings for an organization. Data are used to determine if healthcare performance meets the expected goal (e.g., the number of patients with blood pressure in control). Data are used to measure performance quality that is valued by purchasers of care, accreditation agencies, governing bodies, the general public, and providers of healthcare ([Carey, 2003](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml?favre=brett#ref2)). A clear understanding of the context or goal related to data measurement is necessary for interpretation. For example: What is the measureable goal? Why was that goal selected? Are we striving to meet a defined requirement; a minimum standard, or a long-term goal?

By itself, data do not require a nurse to take action. Consider the following: A heart rate of 60 is an isolated piece of data from one assessment finding. By itself, the heart rate data point of 60 looks good. As healthcare workers, we do not usually base any changes on one piece of data, unless it indicates a critical change or value. If we look at heart rate readings over time (e.g., the heart rate is taken twice a shift for 1 day providing six pieces of data), we can see if a trend exists. A trend looks at changes in data over time. If the six heart rate readings were 110, 100, 90, 80, 70, and 60, we would have information. **Information** is analysis of collected data that is used to make decisions. As nurses, information is used to make nursing care decisions. In the heart rate example, the trend provides information that the heart rate has steadily fallen over three shifts. The nurse needs to decide if action is needed, such as informing the provider of the trend, reviewing medications or changes in medications over the past three shifts, or monitoring the patient more closely to watch for any other assessment changes.

Patients can provide both subjective and objective data. **Subjective (patient) data** are reported by the patient. For example, a patient may state pain status as “5” on a scale of 1 to 10. **Objective (patient) data** may include what the healthcare worker can see or measure, such as the patient’s blood pressure or blood glucose results. Both subjective and objective data are collected, analyzed, and interpreted as information. This information is used to make clinical decisions about whether the patient is getting better, worse, or if the information requires provider notification.

**Sources of Objective Data for QI**

Nurses are inundated with data, representing patient, unit, or organization performance outcomes. **Internal data** are those found within a healthcare organization and are generated by staff, such as falls and medication errors. **External data** are data provided from outside sources (e.g., state quality review organizations) that evaluate and report on the organization’s internal processes and outcomes. **Baseline data** are the preintervention data measurements that are used to identify a problem needing improvement. **Postintervention data** are the changes from baseline data after an improvement intervention and confirm the success or failure of the intervention. For example, a team is working to decrease the number of hospital-acquired pressure ulcers (HAPUs). The average number of HAPUs was six per month for the last 3 months. Six HAPUs represent baseline data. Because six HAPUs were unacceptable, a QI intervention to reduce HAPUs was instituted. After the QI intervention, the average number of HAPUs was three per month, or a reduction of 50% in HAPUs over a 3-month period. Three HAPUs represent the postintervention data. Although a 50% reduction occurred, the team must analyze the postintervention data into information and decide if three HAPUs is acceptable or if further improvement is needed.

When data are collected internally, it is important to distinguish between incidence and prevalence data. Incidence and prevalence data both typically use a quarterly or 3-month time frame. A quarter is 3 months. **Incidence** data are the actual counts of every event that occurred during a specific time frame. For example, counting the number of falls that occurred on a medical–surgical unit for one quarter. **Prevalence** data are a snapshot of event under measure during one day. For example, counting the number of falls that occurred on one specific day during the quarter. To illustrate further, suppose the prevalence rate was measured on one specific day and no fall occurred on the specific date of measurement. The prevalence rate would be zero. Now suppose over the same 3-month period, the actual incidence of falls was 11. Based on how the data were collected, either incidence or prevalence, it can result in dramatically different outcomes. It is important to understand the difference between incidence and prevalence data as organizations may report either depending on their preference or on external reporting requirements. For example, the National Database of Nursing Quality IndicatorsTM (NDNQI®) requires reporting of pressure ulcers as prevalence data ([Hart, Bergquist, Gajewski, & Dunton, 2006](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml?favre=brett#ref6)). In the example regarding HAPUs, because both the baseline and postintervention data were actual numbers of HAPUs over a 3-month period, both data points represent incidence data. If the number of HAPUs was a snapshot on a given day, that would have represented prevalence data. Appreciate that regardless of the type of data, incidence or prevalence, analysis of the data into information for clinical decision making must occur for data to be useful. useful.

**Aggregate Data**

When subjective and/or objective data are collected for process improvements or to assess care delivery, such as HAPUs, it is necessary to ensure that no patient identifiers are captured linking outcomes to specific patients, families, or staff. This will help to protect privacy and confidentiality of data. QI projects generally use **aggregate data**, which are large, grouped data without patient identifiers. These aggregate data, often listed in a table format, may be grouped by time, cause, diagnosis, or the variable being studied. An example of a study variable can include the staff’s adherence to hand hygiene practices, as seen in [Table 14.1](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#tab14_1). In [Table 14.1](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#tab14_1), nursing hand hygiene compliance data are reported in aggregate form that compares three units over a 9-month period. Notice that there is no ability to identify which staff was in or out of compliance during measurement based on the aggregate data.

In [Table 14.1](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#tab14_1), the use of bolding (met the target) and shading (did not meet the target) helps to quickly identify areas needing improvement when looking at large numbers of aggregate data.

**Operational Definitions**

An essential part of looking at any data is to have a clear definition of what is being measured to ensure that everyone is measuring the same thing. An **operational definition** describes in detail what is being specifically measured, how it is being measured, who will measure it, and when measurement should occur.

It is important to know how the data for QI activities are defined, collected, including who can collect the data and when using clearly defined operational definitions. Because many staff may be collecting the data at different time points, having one clear operational definition ensures that the data are collected and measured the same way, regardless of where the data are collected or who collects the data. For example, in [Table 14.1](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#tab14_1), we looked at aggregated data on hand hygiene compliance from three different medical–surgical units. To make sure these data are collected and measured the same way on all units, we would need to state the following in the operational definition: the definition for hand hygiene, who is to collect the data, when the data are to be collected, the number of hand hygiene observations expected, and when the results are to be reported and to whom. Once these variables are known, a numerator and denominator can also be defined. An example of an operational definition and the numerator and denominator is provided as follows:

Hand hygiene, a required organizational measure related to patient safety, is defined as compliance with the Centers for Disease Control and Prevention (CDC) hand hygiene guidelines accessible at www.cdc.gov/handhygiene/providers/guideline.htm. Each unit will identify a “secret” observer on each shift who will monitor hand hygiene compliance for that unit on the first day of each month. Each observer will assess at least 10 interprofessional staff on the unit by observing their hand hygiene during interactions with patients. Results of compliance with CDC hand hygiene guidelines will be reported to the infection control staff within 48 hours of observation. Infection control staff will aggregate the observations as follows:

Numerator: Total number of hand hygiene observations, for example, 45

Denominator: Total number of observations that followed CDC hand hygiene guidelines correctly, for example, 39

Example Answer: 39 hand hygiene observations were correct out of 45 hand hygiene observations (87% compliance)

In this example, there is a clear numerator and denominator for reliable measurement. It can be challenging to develop a clear operational definition to guide a sustainable, consistent process for data collection among the observers.

**CRITICAL THINKING 14.1**

*Select the best operational definition for a fall and explain why you selected the option.*

**1.**A “fall” is defined as the number of patients who fall and for which an incident report is completed. The patient safety officer will collect the data and report them to the Unit Practice Council annually using a control chart.

**2.**A “fall” is defined as the number of patients admitted to the unit who fall and who suffer no injuries, whether minor (e.g., a laceration) or major (e.g., fractured hip). All such incidents will be reported using electronic incident reporting procedures per policy 101-5.

**3.**A “fall” is defined as any patient who falls that results in no injury, a fall that results in a minor injury (laceration), or a fall that results in a major injury (fractured hip). All such incidents will be reported using electronic incident reporting procedures per policy 101-5. The fall numerator is the number of falls and the fall denominator is the total number of patients on the unit during the measurement period.

**Data Collection**

Data are only useful when collected rigorously, meaning that data collection tools must be valid (measures what it is supposed to measure) and reliable (consistently measuring what it is supposed to measure). To illustrate, in the hand hygiene compliance example, although all staff are expected and taught to follow hand hygiene compliance, every “secret” observer should complete additional training on the CDC guidelines and demonstrate competency in hand hygiene compliance before monitoring and observing other staff. The additional training can secure validity by helping the observer accurately measure if hand hygiene compliance occurred according to the CDC guidelines (validity). A second trained observer can observe the first observer to compare both observers, concluding the results comply with the CDC guidelines. By doing this, the second observer is helping to establish reliability of data collected by the first observer on hand hygiene compliance. **Interrater reliability** (IRR) is a process that provides evidence that those collecting data are applying the CDC guidelines correctly to determine if the staff is following the guidelines correctly or not. When IRR exists, the data are considered reliable because data are collected consistently. Conducting IRR may identify observers who need additional education in the interpretation and application of the CDC hand hygiene guidelines, a lesson to learn before hygiene compliance data are reported. One type of data collection error is identifying that a problem exists when in fact there is not a problem. For example, hand hygiene compliance may include using both a hand sanitizer and when indicated soap and water. If the trained observer misunderstood the definition of hand hygiene compliance and only counted the instances where the healthcare worker used soap and water, the findings would be inaccurate. In this case, the number of healthcare workers that used the waterless hand sanitizer was not counted causing a decrease in the percent of hand hygiene compliance. When the trained observer reports the observations, one could easily be concerned that hand hygiene compliance needs improvement when in reality it may not!

Another interpretation of error can also occur. Let us say the trained observer misunderstood the hand hygiene guidelines and interpreted them to say that the only time the healthcare worker had to use the hand sanitizer or wash his or her hands was if the worker touched the patient. The trained observer would then only count compliance when the patient was touched and hand hygiene was completed, missing the fact that hand hygiene should be completed every time the healthcare worker enters and leaves the room. The hand hygiene compliance rates would not clearly identify if any hand hygiene practices need improvement.

**CASE STUDY 14.1**

Two nurses have agreed to collect data on a QI project to decrease the number of patients who cancel their clinic appointments at two different surgical clinics. These patients are called clinic no-shows. The nurse manager over both clinics asks the two nurses to ensure IRR. Not being familiar with the concept of IRR, the nurses look to the literature and discover that this term indicates that those collecting data should be following the same data collection procedures. The nurse manager requests a written plan to ensure IRR between both nurses at the two clinics. How would you write this plan and ensure both nurses are measuring their clinic no-shows consistently?

**DESCRIPTIVE STATISTICS**

Descriptive statistics are tools used to analyze and summarize relationships among variables. Statistics can identify significance within the data and relationships between variables ([Nelson, Batalden, & Godfrey, 2004](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml?favre=brett#ref9)). **Descriptive statistics** are used to define and describe a set of data. For aggregate data, descriptive statistics are commonly calculated and include the mean, median, mode, range, and standard deviation (SD) of a set of data. Review the data displayed in [Table 14.2](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#tab14_2). Note how the mean, median, mode, and range are calculated given a set of data. Determine the **mean** or average of a set of numbers by adding all the numbers together and then dividing by the total number of observations. In looking at hand hygiene compliance for Unit A, note that there are 9 months of hand hygiene compliance percentages reported. The mean compliance for Unit A is calculated by adding all findings and dividing by 9, the number of months. [Table 14.2](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#tab14_2) demonstrates the calculation of mean for Unit A.

An example of a mean that you may be familiar with is your grade point average (GPA). A common GPA scale: A = 4 points, B = 3 points, C = 2 points, D = 1 points, and F = 0 points. If you took all of your grades earned in one semester over the time spent in college and converted the grades to point values as described, you could calculate your GPA using the illustration from [Table 14.2](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#tab14_2). For example, if you took five courses and received one A, two Bs, and 2 Cs, your GPA would be calculated as 4 + 3 + 3 + 2 + 2 = 14/5 = 2.8 GPA.

The **median** of a set of data is determined by listing the hand hygiene findings from lowest to highest values. Once listed, the median is the value at the separation point, where half of the data is above and the other half below the data point that falls within the middle of the set of data. To illustrate, here are five data points arranged from lowest to highest: 4, 6, 11, 13, and 15. The median is 11 or the middle number of the set as there are two data points before and after 11. When there is an even number of results, the median is the average of the two middle results. For example, if the values were 4, 6, 7, 11, 13, and 15, the median would be 9, the average of 7 and 11, or 18/2 = 9. [Table 14.2](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#tab14_2) illustrates the median, or 80%, for hand hygiene compliance on Unit A. The median statistic is used less frequently than the mean in statistical QI work.

In QI activities, the mode is of less use compared to the other descriptive statistics but it may be included in analyses, therefore it is useful to define. The **mode** is simply the value that is repeated most frequently in a set of data or the “typical” value observed. To illustrate this, refer to [Table 14.2](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#tab14_2). Note the value 80 is repeated.

The **range** represents the lowest and highest values in the data. Reviewing the range of data is a quick measure of **variability**. Variability refers to the differences between the numbers in a data set. A simple measure of variability can be determined by observing the range of a data set.

[Table 14.2](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#tab14_2) illustrates the range of values for Unit A from 69 to 91. Knowing data variability helps you to identify just how far apart the data are. Consider this: You are working on a QI project to reduce falls. Over 12 months, one unit had a high of 13 falls and a low of zero falls. The variability shows you that the unit is not consistent in reducing falls, unless, of course, it went from 13 to 0 over time as the result of continuous improvement.

The most common method used to describe the variability of a data set is **SD**, which reflects how “tightly” the data points cluster around the mean as seen in [Figure 14.1](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_1). SD is often abbreviated as the Greek letter sigma (**s**). In a “normal” distribution of a data set, most measures hover around the mean while a few measures tend to be at opposite extremes from the mean. In a SD curve, the mean is located at the center of the graph and is represented as 0 in [Figure 14.1](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_1). In a normal distribution, it is expected that 68.3% of outcomes will fall within one SD above or below the mean (+1/-1). Another 27.1% of outcomes should fall within two SD from the mean (+2/-2) accounting for 95.4% of all expected outcomes. An additional 4.2% of outcomes should fall within 3 SD from the mean (+3/-3), which accounts for 99.8% of all outcomes.

Note that, if 20 students completed a test with a mean score of 80%, it is expected that most of those students (68.3%) would hover around an 80% score. More, or 95.4%, of students would be expected to fall within two SD of 80%, and even more (98.8%) of students would fall within three SD from the mean. SD of a set of data can be easily calculated using software such as Microsoft Excel®.

As seen in [Figure 14.1](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_1), outcomes (99.8%) are expected to fall within three SD of the mean. Variability in a data set is an important concept in QI activities and are further examined with SPC later in the chapter. For practice calculating basic descriptive statistics refer to Case Study 14.2.

You have just completed data collection on a QI project to reduce calloffs on your unit. To obtain calloff baseline data, you have been asked to document the number of calloffs over a 3 week period to identify the number of calloffs more prominently for each shift. Your results are listed as follows:

Week 1: (Days) 3 (Evenings) 1 (Nights) 1

Week 2: (Days) 4 (Evenings) 2 (Nights) 2

Week 3: (Days) 1 (Evenings) 3 (Nights) 1

Now that you have your outcomes, calculate the mean, median, mode, and range of these results.

**DATA DISPLAY**

Data are visible in all healthcare settings. It is difficult to walk onto an inpatient or outpatient area without seeing data. It is necessary, however, to analyze and interpret data into usable information. **Data display** refers to a visual picture or graphing of data that best depicts the story you want that data to exhibit. Data should be displayed in ways that staff, patients, and families can understand. Figures, graphs, and tables are acceptable methods of displaying data. Whatever the format, data must include a clear title of what is being presented, including the use of footnotes to clarify aspects of the table or figure ([Nelson, Batalden, & Godfrey, 2004](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml?favre=brett#ref9)). For example, footnotes may be useful to define a column title, or to refer the reader to the operational definition of a specific value. Recall [Table 14.1](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#tab14_1), hand hygiene compliance for three nursing units. For easier interpretation, those months meeting the targeted goal of 90% were highlighted while those not meeting the goal were shaded.

Data alone do not always offer guidance regarding improvement priorities. For example, looking at [Table 14.1](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#tab14_1), Unit B lists outcomes for May (79%) and June (59%). Does this decrease in compliance require immediate attention? A “yes” response may be premature. In fact, the answer to that question should not be determined by comparing two results alone as two results may not provide enough data for analysis and decision making. Fortunately, more sophisticated methods are available to better inform improvement decisions. As you will learn, visually displaying data over time is useful when assessing outcomes to better inform if interventions are needed, if improvement occurred, or if improvement was sustained.

When data are generated, they must be interpreted as meaningful information. For example, in [Table 14.1](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#tab14_1), if Unit B wanted to improve its hand hygiene compliance rate (mean = 53.5% over 9 months), some change or intervention must be implemented. Recall that 53.5% or the baseline measure will be compared to the postintervention percent compliance to determine if the intervention worked. At this point, we have only discussed data. We now look at how data are displayed in various graphical formats. Our discussion focuses on commonly used formats including a histogram, scatter plot diagram, and Pareto charts, as well as run and control charts. Note that when data are plotted within a graph, the horizontal axis of the graph is referred to as the *x*-axis and the vertical axis of the graph as the *y*-axis.

**Histograms**

A **histogram**, as seen in [Figure 14.2](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_2), is a bar graph that displays the data. Data displayed using a histogram allows for easier visualization of large, aggregate data that may originate from a table. To understand a histogram, it is important to know the *y*-axis and *x*-axis. The *y*-axis is the vertical line and is easily remembered as “*y* to the sky.” The *x*-axis is the horizontal line and can be remembered as “*x* to the left.” Histograms are useful in determining patterns within historical data or displaying baseline data. In [Figure 14.2](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_2), the histogram uses a bar to display the lengths of stay for the last 50 admissions.

The number of admissions is located on the vertical *y*-axis. The variable along the horizontal *x*-axis (lengths of stay in days) is sequential starting with the shortest to the longest length of stay. The most frequent average length of stay (14 observations) is between 3 and 4 days. Histograms are easily made with or without software and quickly depict the distribution of a set of data or outcomes.

**Scatter Plot Diagrams**

**Scatter plot diagrams** display relationships between two variables by providing a visual means to test the strength of the relationship between the two variables. The design of the dots within the scatter plot diagram is used for interpretation. Several designs can be depicted when observing the scatter plot diagram, a positive, negative, or no relationship design. Examples of each scatter plot design are depicted in [Figure 14.3](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_3). The scatter plot looks at two variables, or issues, that you want to look at. A relationship between the two variables does not indicate that one variable caused the other. The scatter plot assists in determining if a relationship exists.

Consider the length of stay data displayed in the histogram in [Figure 14.2](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_2). The relationship between the variable of length of stay could be compared to another variable, such as patient satisfaction using a scatter plot ([Figure 14.3](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_3)).

The scatter plot diagram in [Figure 14.4](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_4) illustrates the relationship between lengths of stay (in days) and patient satisfaction scores using a Likert scale ranging from 5 to 1, where 5 is most satisfied, 3 is neutral, and 1 is least satisfied. In [Figure 14.4](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_4), the design of the scatter plots indicates there is no relationship between length of stay and patient satisfaction for the 50 patients in this sample.

**Pareto Charts**

The Pareto chart is another type of bar graph. It is similar to the histogram because it depicts how often data represent a particular value. The difference between a histogram and a Pareto chart is that the **Pareto chart** orders findings in a descending order from high to low with the most frequent issue contributing to the results furthest to the left on the *x*-axis. Visualizing results from high to low allows prioritizing, or identifying what data most impact the variable in question. One benefit of the Pareto chart is in demonstrating the Pareto principle that 80% of the problem comes from 20% of the causes. When the causes of problems are ranked in order of effect on the QI problem, you can clearly identify those causes having the greatest effect. The Pareto chart in [Figure 14.5](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_5) illustrates that tardiness of the oncoming shift, furthest to the left, is the most common cause of unit overtime during a 1 month period.

In [Figure 14.5](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_5), the four most common causes of overtime, that is, tardiness, turbulence, hand off delays, and staffing pattern, are ranked from high to low as you read from left to right. These four causes represent 81% of the problems leading to overtime. You can look above the column labeled “staffing patterns” and see where the line marks 81% of the problems. These four causes will serve as target problems needing improvement to reduce overtime costs. The manager can easily visualize, prioritize causes, and plan improvement interventions to reduce overtime usage based on review of the Pareto chart. Appreciate that the leading cause of a problem may not be the focus of improvement. In this example, if meeting with the Employee Health Department has been the greatest cause of overtime, it may not be feasible to address since the manager of the unit may have little control over employees appropriately seeking Employee Health services. Or, looking at that scenario from another perspective, if meeting with Employee Health services was the greatest cause of the overtime, you may want to do a root cause analysis (RCA), fishbone diagram, or ask the five Whys discussed in [Chapter 13](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_13.xhtml#ch13) to determine why there is so many more staff than usual seeking Employee Health services and driving up overtime usage.

**STATISTICAL PROCESS CONTROL**

Thus far, we have illustrated figures and tables commonly used to analyze and represent data. In the Pareto chart depicted in [Figure 14.5](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_5), tardiness is the most significant cause of overtime. However, the chart does not illustrate any change from previous months. Perhaps calloffs were once the most frequent cause of overtime but are now reduced? Perhaps these causes of overtime are changing month to month? The Pareto chart categorizes factors leading to specific outcomes, however, these data are mainly a snapshot of what existed at the time the data were collected ([Grube, 2008](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml?favre=brett#ref5)). Other approaches exist that depict data trends over time that allow for improved decision making and prioritization. SPC is an approach for analyzing data adding science to QI decision making ([Nelson, Batalden, & Godfrey, 2004](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml?favre=brett#ref9)). SPC uses statistical methods to monitor and control quality processes to reduce or eliminate waste. This chapter will only introduce you to and cover the basics of SPC as they apply to QI projects.

SPC adds the ability to identify variation within a process ([Evans, 2008](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml?favre=brett#ref3)). **SPC** is a type of statistic that, when applied, demonstrates a statistical approach to QI decision making. SPC is used to monitor a process over time (time-series design) but adds the ability to identify variation within that process by plotting data points within a run chart or control chart.

In [Figure 14.5](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_5), after identifying tardiness as the major contributing factor to overtime, it would be valuable to apply principles of SPC to assess variability in the causes of overtime and identify the need for change. For example, 15 causes of overtime in [Figure 14.5](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_5) were from tardiness. Is this a new outcome? Was tardiness noted only twice last month and suddenly increased? Is tardiness a priority to improve or are there other competing processes needing attention first? SPC depicts process variability, the degree to which the process is stable or unstable over time. Think about the hand hygiene data in [Table 14.1](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#tab14_1). Any change in the percent of hand hygiene compliance from one month to the next month is variability. In [Table 14.1](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#tab14_1) data are presented in a time series, from January through September. However, data displayed in tables do not allow for analysis beyond descriptive statistics. Could the hand hygiene data represent an unstable hand hygiene process, meaning the data fluctuate unpredictably over time? These are important questions answered by applying SPC when analyzing data. In order to answer these questions, the concepts of common cause and special cause variation must be understood.

On any given day, your lunchtime may vary anytime between 11 a.m. and 1 p.m. This is an expected variation, referred to as **common cause variation** or “noise,” the inherent variability seen in a stable “in control” process ([Carey, 2003](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml?favre=brett#ref2)). If one day an emergency prevented you from eating lunch until 3 p.m. that time point is very different from your expected lunchtime. Lunch occurring between 11 a.m. and 1 p.m. is expected. When a data point varies significantly in an unpredictable or unexpected manner, it is referred to as **special cause variation**, which signals that something happened (an emergency occurred) that changed the process for better or worse and that the process is “out of control” ([Carey, 2003](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml?favre=brett#ref2)). Because all processes have inherent variation, such as lunch between 11 a.m. and 1 p.m., determining common cause from special cause variation is important. The risk of not knowing if common cause or special cause variation exists is that common cause variation may be prioritized for improvement when improvement is not warranted. Additionally, when special cause variation is identified, that raises a red flag that the process is no longer in control, which may need immediate attention.

Assessing for common cause and special cause variability captures the essence of SPC, or being able to look at data over time to determine the type of variability that exists. Both common cause and special cause variation require further interpretation. When special cause variation is found, efforts should focus on identifying an explanation of what occurred that resulted in the process being out of control. If the process exhibits common cause variation, it may not need improvement. When common cause variation exits, the analysis must include answering the question if the process is performing at an acceptable or desired level. Just because the process is under control (common cause variation) does not mean the process could not be improved to a higher level of performance. For example, say hand hygiene data that illustrate compliance to the CDC hand hygiene guidelines was measured monthly for a home healthcare team. The annual mean of compliance was reported as 65%, within common cause variation. Although 65% is within common cause variability, the question remains if 65% is acceptable. If it is not, an improvement could be recommended. If it is not but other priorities for improvement take precedence, working to increase hand hygiene compliance may need to wait.

In SPC, assessing variability requires use of formats such as the run chart ([Figure 14.6](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_6)) or Shewhart control chart ([Figure 14.8](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_8)). Because the goal is to reduce variation within processes and to sustain that over time, there is considerable movement in healthcare to use SPC as a QI methodology when analyzing outcome data ([Mohammed, Worthington, & Woodall, 2008](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml?favre=brett#ref8)). Both the run chart and the Shewhart control chart are tools used to assess process variation.

**The Run Chart**

The run chart depicts data in a time series format where an outcome variable, for example, compliance to hand hygiene CDC guidelines on the *y*-axis, is plotted on a graph over a period along the *x*-axis. Recall that a time series format refers to the representation of data over consecutive time points. It can be used for any type of data, including measurement and count data created by hand or using software. Characteristic of all time series charts, the *x*-axis (horizontal) represents the period and the *y*-axis (l vertical) represents the variable being measured ([Figure 14.6](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_6)).

**FIGURE 14.6** Run charts demonstrating pain reassessment compliance within 60 minutes of IV pain medication administration for three units.

The purpose of a **run chart** is to identify trends in a process or movement away from a central point, such as the median. The run chart allows teams to assess how a process is working. The process can be routine, such as assessing pain reassessment post IV pain administration or assessing a new process implemented for improvement. Simply stated, the run chart is a visual display of a process performance.

The run charts depicted in [Figure 14.6](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_6) show how the data are organized. The time frame being shown is 12 months (*x*-axis) in chronological order. The outcome variable, percent compliance of pain reassessment, is seen on the *y*-axis. When using SPC, the range of percent will vary by unit based on each unit’s outcomes. This is illustrated in [Figure 14.6](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_6), where Unit A has a range between 48% and 75% (lowest point and highest point) and Unit B has a range between 30% and 71% (lowest point and highest point). You may choose to include a table of the raw data within the run chart for additional detail. Expert opinions vary, but generally 12 to 16 time points are adequate for statistical differentiation. In addition, more than 25 time points will not increase the statistical power ([Carey, 2003](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml?favre=brett#ref2)). The median or middle point of the data set is used as the centerline on run charts because it is not sensitive to **outliers**, like the mean may be. As seen in [Figure 14.6](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_6), the mean compliance of pain reassessment post IV pain medication administration for Unit A is 58%. Recall that the median is calculated by first arranging the data from low to high (48, 49, 50, 52, 52, 54, 62, 66, 69, 70, 72, 75). Because the median is the middle point and there are 12 time points on the graph (October to September), the sixth (54%) and seventh (62%) data points are added and divided (54% + 62% = 116/2 = 58%). In assessing the run chart, first consider if the data are hovering close to the median line or if the data are spread inconsistently from the median. If the data points hover close to the median, the process variation is minimal. If the data are inconsistently away from the median line, that represents greater process variation. When data points fall significantly above or below the median line, an outlier or an unusual finding exits. Now, look at Unit C in [Figure 14.6](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_6). The median center line is at 49%, which was determined by the raw compliance percent in chronological order from low to high: 43, 43, 44, 44, 44, 47, 51, 55, 55, 60, 60, and 62. Because we have an even number of data points, the two middle points (47 and 51) are averaged (47 + 51 = 98/2 = 49%).

The run chart is useful in determining QI potential. When using a run chart, there is no true statistical analysis occurring in comparison to the control chart discussed in the following section. However, the run chart allows for quick analysis and visual review of how a process is performing. Looking back at [Figure 14.6](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_6), does any unit’s data demonstrate an outlier or finding different from the others? If you said Unit B, you would be correct. With a median of 65% compliance, the 30% compliance seen in March is an outlier. In general, Unit B is relatively stable with most compliance scores hovering around the median line, except for March, which was a drastic drop from February (64%). Unit B should ask, what happened in March? Is there an explanation for this change? Perhaps Unit B was orienting new nurses who were not yet familiar with the pain policy. Also notice the improvement in April (70%). Is this improvement based on a QI intervention or did the new nurses become familiar with the pain policy? Before mobilizing resources to improve an outlier representing special cause variation, first determine if there is an explanation. If so, monitor the unit for the next few months to determine if that outlier was incidental or if there actually is a problem needing QI intervention. If one special cause data point cannot be explained that might place patients at risk, further QI intervention is needed.

How would you compare the three units in [Figure 14.6](https://jigsaw.vitalsource.com/books/9780826123855/epub/OEBPS/text/9780826123855_Chapter_14.xhtml#fig14_6) regarding their compliance with pain reassessment? Unit A was below the median for the first 6 months then steadily improved over the last 6 months. What is not known is if the unit implemented a QI intervention in March with the following 6 months demonstrating positive improvement. If an intervention was implemented it should be sustained and celebrated. Also unknown is if the change from April (48%) to May (62%) was special cause variation.

With the additional subsequent data points in June and September, it appears that the pain reassessment process changed for the better and that improved performance is being sustained. One challenge when interpreting a run chart for outliers or determining at what point on the chart the data represent the outlier is that this is subjective. You will see subjectivity is eliminated by using the control chart, described in the following section. Unit B’s process has been in control except for that one special cause finding in March. Unit C demonstrates lots of variability in outcomes. There is little consistency month to month. Although no special cause can be clearly defined, a QI intervention may be needed to reduce or explain the process variation that is illustrated. When comparing units or process outcomes, establishing the goal or target that demonstrates a success process not needing improvement is necessary, as discussed as part of the operational definitions earlier in this chapter. If the goal is 90% compliance, no unit in Figure 14.6 is meeting the goal. It may be helpful to include the goal on the run chart. Additionally, relative internal and external comparisons can provide benchmarking opportunities. For example, organizations may wish to compare their outcomes to other organizations and such comparisons could be used to determine if one organization is performing at a different level than another. Table 14.3 summarizes types of variation, analysis considerations, and potential QI actions. Prioritization is based on the volume and criticality of the outcomes and should include the consensus of QI experts and staff involved in the process. The run chart is helpful to determine improvement priorities and actions to be taken based on analysis. Additionally, although Unit C might like to reduce its variation, the reality is other more critical problems may require attention first. One advantage of using a run chart is its ease in interpretation; run charts are commonly used by healthcare organizations. One disadvantage is that it is not as statistically sensitive as other tools with more specificity (Lloyd, 2010). There is another type of chart, the Shewhart control chart, commonly referred to as the control chart, described in the following section that adds a statistical advantage to the run chart that clearly detects outliers or unusual findings and eliminates the need for guessing. It takes time and practice to interpret run charts. For a closer look at interpreting a run chart, refer to Case Study 14.3.

TABLE 14.3 VARIATION INTERPRETATIONS, ANALYSIS, AND QI ACTIONS TYPE OF VARIATION ANALYSIS QI ACTIONS Common cause variation (process in-control) Is the process demonstrating acceptable variation/acceptable level of performance? No QI actions is required Is the process in control but a wide range of or unacceptable variation exists? QI actions may be required based on QI priorities Special cause variation (process out-of-control) Is the process statistically demonstrating a problem, a change that is not desirable? Action is required Is the process statistically demonstrating improvement based on QI efforts? Continue to monitor to determine if efforts are sustained over time; if so, spread the lessons learned QI, quality improvement. CASE STUDY 14.3 Use the data from Figure 14.6. At a Unit C QI meeting, a nurse asks for assistance interpreting if the unit improved their pain reassessment compliance. The nurse notes that the first 3 months’ results are October: 52%, November: 45%, and December: 50% (Figure 14.6, Unit C). How would you respond as to whether the pain reassessment compliance improved or did not? The Shewhart Control Chart The Shewhart control chart, often referred to as simply a control chart, is the same as the run chart but it adds statistical control limits to the run chart using SD. Because SD is used, the centerline is represented by the mean of the data set rather than the median that is seen on the run chart. The x- and y-axis are set up the same on both charts, with the x-axis being the time points and the y-axis being the variable or process under study. The Shewhart control chart has the same purpose as the run chart, that is, to distinguish common cause from special cause variation. Recall the discussion about SD and that “sigma” is another term used for SD. The Shewhart control chart, created by software such as QI Macros®, will set SD control limits at 1, 2, and 3 SD above and below the mean of the data set. The advantage of the Shewhart control chart is the addition of SD because there is no guessing if an outlier or abnormal data point is present, which will be demonstrated shortly. When analyzing a Shewhart control chart, the upper control limit (UCL) is defined as the line 3 SD above the mean while the lower control limit (LCL) is the line 3 SD below the mean. A process that is considered to be in control or demonstrating common cause variability will have all data points between the UCL (+3 SD from the mean) and LCL (-3 SD from the mean). Together, the upper and lower control limits represent Six Sigma. When a data point falls above or below the UCL or LCL, the process is said to have a statistically significant outcome, referred to as special cause variation, or abnormal finding. Before examining the Shewhart control chart, it is a good time to think about what we have already learned. Data can be displayed using a variety of formats, including histograms, Pareto charts, run charts, and Shewhart control charts. Each format has a purpose and a value within QI. Consider the Pareto chart in Figure 14.7. These data represent the annual incident reports of a large multisite organization. Medication errors are the leading cause of incident reports over a 12-month period. That outcome could trigger a QI activity. However, we now know there are more sophisticated SPC methods available to better analyze these incident report data. In Figure 14.8, aggregate medication errors are shown on a Shewhart control chart using a time series design over 12 months. A range of outcomes, in this case from eight to 37 medication errors, is depicted, which represents significant variation. In analyzing aggregate medication errors in Figure 14.8. What do you notice different in the control chart as opposed to a run chart? The major difference includes the addition of the UCL and LCL, which can be used to analyze the process range. Because nearly 100% (specifically 99.8%) of outcomes are expected to fall within three SD from the mean, as seen in Figure 14.1, using three SD is generally considered acceptable when analyzing for special cause variation.

In Figure 14.8, the UCL was established at 22.2 and the LCL at 4.5 automatically using the QI Macros software. FIGURE 14.7 Incident report data over 12 months using a Pareto chart. FIGURE 14.8 Aggregate incident report data over 12 months using a Shewhart control chart. Evaluating the UCL and LCL is valuable because these limits specify the process range. As illustrated in Figure 14.8, the mean of aggregated medication errors over the 12-month period was 13. The UCL or 3 SD above the mean is 22 while the LCL or 3 SD below the mean is 4.5. The significance of this is that anywhere between 22 and 4.5 medication errors could occur each month and be considered in control, or within Six Sigma of the mean. In this case, that alone might trigger a QI activity as 22 medication errors a month while being considered in control would be concerning from a patient safety perspective. Also note in Figure 14.8 the centerline is the mean of the data points in a Shewhart control chart, whereas the centerline on a run chart is the median of the data set. There are several different types of Shewhart control charts and their interpretation rules. At this point, it is important to apply the same rule used with the run chart, that is, identifying if an outlier or unusual data point exists. With the Shewhart control chart, your job is made easier in this analysis as special cause is evident when a data point appears either above or below the control limits. Analysis and QI actions taken based on the interpretation of the run chart outlined in Table 14.3 also apply to the Shewhart control chart: 37 incidents in April is nicely depicted significantly above the UCL in Figure 14.8. There is no guessing required if the data point represents special cause variation as it is above the UCL of 22. The Shewhart control chart reduces interpretation errors and the risk of not implementing QI activities when necessary or implementing QI activities when not necessary, leading to inappropriate resource utilization. In addition, notice that the number of medication errors was significantly reduced in the month of May to eight and remained hovering around the mean of 13 through September. This is a good example that when an unusual outcome occurs, such as 37 medication errors in April, it may be advantageous not to react and implement a QI activity but rather to acknowledge the outcome, continue to assess it, and follow the trends to determine if the number of medication errors continue to rise over time that would demonstrate statistical significance by being above the UCL.

Evaluating the UCL and LCL is valuable because these limits specify the process range. As illustrated in Figure 14.8, the mean of aggregated medication errors over the 12-month period was 13. The UCL or 3 SD above the mean is 22 while the LCL or 3 SD below the mean is 4.5. The significance of this is that anywhere between 22 and 4.5 medication errors could occur each month and be considered in control, or within Six Sigma of the mean. In this case, that alone might trigger a QI activity as 22 medication errors a month while being considered in control would be concerning from a patient safety perspective. Also note in Figure 14.8 the centerline is the mean of the data points in a Shewhart control chart, whereas the centerline on a run chart is the median of the data set. There are several different types of Shewhart control charts and their interpretation rules. At this point, it is important to apply the same rule used with the run chart, that is, identifying if an outlier or unusual data point exists. With the Shewhart control chart, your job is made easier in this analysis as special cause is evident when a data point appears either above or below the control limits. Analysis and QI actions taken based on the interpretation of the run chart outlined in Table 14.3 also apply to the Shewhart control chart: 37 incidents in April is nicely depicted significantly above the UCL in Figure 14.8. There is no guessing required if the data point represents special cause variation as it is above the UCL of 22. The Shewhart control chart reduces interpretation errors and the risk of not implementing QI activities when necessary or implementing QI activities when not necessary, leading to inappropriate resource utilization. In addition, notice that the number of medication errors was significantly reduced in the month of May to eight and remained hovering around the mean of 13 through September. This is a good example that when an unusual outcome occurs, such as 37 medication errors in April, it may be advantageous not to react and implement a QI activity but rather to acknowledge the outcome, continue to assess it, and follow the trends to determine if the number of medication errors continue to rise over time that would demonstrate statistical significance by being above the UCL. Stratification Stratification is the process of breaking the data down into subsets to better interpret what is happening and where (Fowler Byers & Rosati, 2008). Suppose the Patient Safety Officer is studying Figure 14.8 and prioritizes medication errors for a QI project. Before moving forward, stratification of the 160 aggregated medication errors could help target where QI efforts should focus. To do so, the 160 medication errors could be stratified into outpatient and inpatient areas. Data could be further stratified among inpatient or outpatient units to better determine if one particular unit is contributing to the abnormal finding. Additional questions should be considered: Were there truly so few errors, except in April? Does all staff understand the reporting process? Is the operational definition of medication errors clear? Does the organization’s culture support reporting medication errors?

CRITICAL THINKING 14.2 You are a nurse in a women’s health clinic assigned to an improvement team with the aim to reduce the rate of the clinic breast cancer deaths. The clinic, located in Boston, Massachusetts, has a breast cancer rate of 10 per 100,000 female patients. Your first assignment is to research how the clinic’s rate compares to the entire state breast cancer death rate. In addition, you have been asked to identify the top five states with the lowest breast cancer death rates as the actions these states may have implemented may be a valuable source of interventions for the project. Go to the AHRQ website: statesnapshots.ahrq.gov/snaps10/index.jsp. Select “State Rankings for Selected Measures”. When clicking on each state, their 2010 National Healthcare Quality Report will open that includes the state’s breast cancer death rate and state rank. Determine how the clinic’s rate compares to the state’s rate. Review each state and determine which states have the lowest breast cancer death rates. OTHER QI TEAM TOOLS Interprofessional teams are often created to bring experts and or process owners together to address problems and make improvements. QI tools, such as those described by Scholtes, Joiner, & Streibel, (2003), Gantt charts, parking lots, and flow maps help teams work through projects. These team tools as well as those discussed in Chapter 13, such as cause and effect or Fishbone diagrams, LEAN thinking, Six Sigma, Plan-Do-Study-Act (PDSA), Health Failure Modes Effect Analysis (HFMEA), and RCA are all QI tools used by teams. Gantt Chart A Gantt chart is a graph depicting the phases of a project over the project’s time line and is used to keep the team on schedule (Figure 14.9). All known project tasks are included in the Gantt chart, from beginning to end. Because QI takes time and effort, line 16 of the Gantt chart in Figure 14.9 nicely reminds us to celebrate and share success, something all teams should include in their planning. Flow Map QI is focused on improving healthcare process; therefore, understanding each step within the process must be considered before interventions are identified. A flow map, or process flowchart, is a visual depiction of a process from the beginning of the process to the conclusion or end of the process and allows the QI team to diagram the actual sequence of activities and decisions within the process. Clarifying the sequence of a process reduces redundancy, unnecessary steps, and may illustrate overly complex processes that can be eliminated. Because healthcare processes are often complex, reducing the number of steps or decisions within a process is not only more efficient but may enhance patient safety. In addition to identifying inefficient steps in a process, flow maps also provide a visual step-by-step flow of a process that may not need to be more efficient but rather to provide a visual tool outlining the steps of a task or procedure. For example, although a nursing procedure such as blood administration will outline a written step-by-step process that the nurse must follow when administering blood, it is not uncommon to include a visual flow map of that process within the procedure.

Different steps or actions within a healthcare process are represented by specific symbols in a flow map, such as ovals to depict the beginning and end points. Squares are used to identify steps in the healthcare process. Diamonds identify decision points, and arrows identify directional flow of the process. Figure 14.10 shows a patient flow map through an ED. We have examined what data are and how data can be displayed for QI decision making and monitoring. Tools, such as those described in the SPC section earlier, provide the QI team with the most efficient, systematic means of determining what healthcare process needs improvement or if a QI was sustained over time. Given the advantages of SPC, these methods should be applied to healthcare decision making whenever possible. Creating and analyzing data using run or control charts require time and practice. Collaborating with QI experts for assistance is recommended. The next step in the QI journey is to empower a team who utilizes appropriate QI tools for data-driven QIs.

I was asked to participate in Lean training. A group from our unit went to the training not knowing what LEAN really referred to. None of us were sure what this LEAN was or what it involved. Content was presented using lots of new terminology. We heard about PDSA but process mapping? Fishbone diagrams? As the program progressed, it became clear that the expectation of the participants was to complete a LEAN project. Although nervous and wondering what did we commit to, we all were intrigued and believed we had lots of ways of making our unit more efficient. We focused on brainstorming, process mapping, flow diagrams, and creating a PDSA. This was enlightening. Here we were flow mapping healthcare processes! What was most exciting was how we might use some of these tools on our unit. We were always so busy just responding to the many demands of patient-care that we seldom took the time to discuss our unit and how we could make things better. We gained insight how to creatively make change. It was an amazing feeling! After the training we were all energized and eager to continue our discussion on a project and to get others on the unit involved. We were successful in creating our first Systems Redesign project using LEAN principles. We all shared similar frustrations with inefficiency in delivering patient care, particularly in our supply areas. Supplies were scattered instead of being grouped together. If a nasogastric tube needed to be inserted, it required travel to four different supply locations. Our large clean supply area was changed due to construction. This gave us the impetus to improve the supply area layout for efficiency using LEAN principles. We tagged unnecessary or duplicate supplies and eliminated them. We collaborated with other departments; had quality experts take pictures so we could compare the before and after changes; we worked with supply staff to consider how we might change the utility room layout, added photos of supplies, and logically arranged supplies together (e.g., oxygen administration supplies were all reorganized to the same bin area; patient-care supplies, pajamas, toothbrushes, urinals, and any personal care items were all relocated in one spot, saving us time and frustration!) What was amazing was our collaboration and success in working with other departments. We interacted with laundry, carpenters, infectious disease, pharmacy, central supply, quality experts, and housekeeping. Our group was on fire. We had actually implemented tools introduced to us in training. None of us ever collected data or worked through an improvement process from beginning to end. Yet we did it and had fun at the same time because we created a positive change for our unit. It has been exciting, overwhelming, and frustrating at times to be involved in such a project. I started off completely unprepared for such an activity. After all, I am just a staff nurse, right? Never would I have imagined taking a lead role in the redesign project and now I can say I contributed to a successful change on my unit. What a journey!

KEY CONCEPTS •Quality improvement (QI) is a continuous process used to prevent, recognize, and reduce harm. It includes the ongoing search for performance excellence. •QI is defined using the Quality and Safety Education for Nurses (QSEN) definition, to “Use data to monitor the outcomes of care processes and use improvement methods to design and test changes to continuously improve the quality and safety of health care systems.” •Quality initiatives are data driven and patient centered. •Many sources of data exist, including internal, external, baseline, postintervention, incidence, prevalence, and aggregate. •Data can be displayed using a variety of formats, including Histograms, Pareto charts, Scatter plot diagrams, and run and control charts). •The science of quality improvement, mainly statistical process control, is concerned with minimizing variability within healthcare processes. •Teams, often interprofessional, bring expertise and innovation to improving outcomes. •Teams can use a variety of tools (Flow maps, Parking lot, and Gantt chart) during the improvement process.

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