Module 1: The Case for Quantitative Analysis

Module One: The Case for Quantitative Analysis

1.01 Learning Objectives

Learning Objectives

After completing this module, you should be able to:

1. Explain why quantitative analysis and analytics is important in decision making
2. Explain the types of decisions that can be made analytically in an organizational setting
3. Describe different decision making models and tools
4. Identify the fundamental concepts of measurement including levels of measurement, reliability and validity, errors, measurement and information bias
5. Explain how quality data affects decision making (GIGO principle)
6. Describe methods of ensuring the quality of data
7. Evaluate techniques for ensuring accurate research design
8. Describe how research is used in different settings: business, education, healthcare, the military, government, nonprofits
9. Explain data management techniques including transforming data, recoding data, and handling missing data
10. Apply appropriate decision making techniques to a specific case

1.03 Video: Introduction to Data-Driven Decision Making

This assignment does not contain any printable content.

1.04 The Rise of Analytics

The Rise of Analytics

No matter what field of endeavor you are involved in—business, education, healthcare, the military, government work, or nonprofits, to name a few—you will likely be asked to make a decision based on data.

Driving that decision making will be quantitative analysis and it will typically focus on statistics. A large set of data in itself is not very valuable unless it can be described and analyzed. Because of the relatively low cost of computer storage and processing power, it is now possible to collect and store vast amounts of data about users of your products or visitors to your website, for example. Statistics can help make the best use of this data.

Retail

Retailers, for instance, may want to analyze historical shopping trends to help in estimating future sales. Or they may want to review prior customer purchases of given products in order to directly promote similar products (through email or direct mail) to likely buyers.

Healthcare

A hospital might want to look at its positive and negative surgery outcomes to compare them to other hospitals or the national average. By going through patient records they can obtain this data, and then analyze it to compare it with industry benchmarks. In fact, there are accreditation organizations that require this information on a regular basis, so it is important for hospitals to perform this analysis routinely.

Coaching

The coaching staff of the university baseball team certainly wants to know how the players on the team perform with home-field advantage in the post-season when the team is losing in the 7th inning. By tracking data on the post-season, on home-field advantage, and on scores, the data can be analyzed to obtain this information.

Many managers and leaders are also turning to analytics. Analytics has been defined by Thomas Davenport and Jinho Kim as the extensive use of data, statistical and quantitative analysis, explanatory and predictive models, and fact-based management to drive decisions and add value.

Analytics can help you make decisions based on hard information, rather than guesswork. Analytics can be classified as descriptive, predictive, or prescriptive according to their methods and purpose.

Descriptive and predictive analytics use past data to project trends in the future. Prescriptive analytics, however, can make use of current and future projected data to make suggestions and help direct your decisions.

Optimization is a prescriptive analytics technique that seeks to maximize a certain variable in relation to another. If, for instance, you want to maximize your factory output while specifically minimizing labor costs, you might employ a model to achieve that goal. The results of your modeling would, in theory, give you the minimum amount of labor needed to achieve the highest possible output.

Descriptive analytics	Depict and then describe the characteristics of what is being studied
Predictive analytics	Use data from the past to predict the future
Prescriptive analytics	Include experimental design and optimization to suggest a course of action

Big Data

The use of quantitative analytics is particularly important in Big Data decision making. Big Data refers to both structured and unstructured data in such large volumes that it's difficult to process using traditional database and software techniques. An example of structured data would be credit card transactions through a website. Examples of unstructured data would be Word documents or the bodies of emails or videos from a traffic accident site—data that doesn't reside in a traditional row-column database format.

The volume of data involved in Big Data is....enormous. For example, Google searches executed by users all over the world averaged over five billion per day in 2012. Consider the number of posts to YouTube or Facebook. Now add in video feeds, voice telecommunications, and text messages, and you can likely understand how companies can be flush with data.

An Example of Analytics—Military Use

In the military, analytics can be used to measure the quality of the equipment used by soldiers, including vehicles, weapons, or body armor. In product development, analytics can be used to establish parameters that new weapons systems must conform to, or they can assess the efficacy of new training methods.

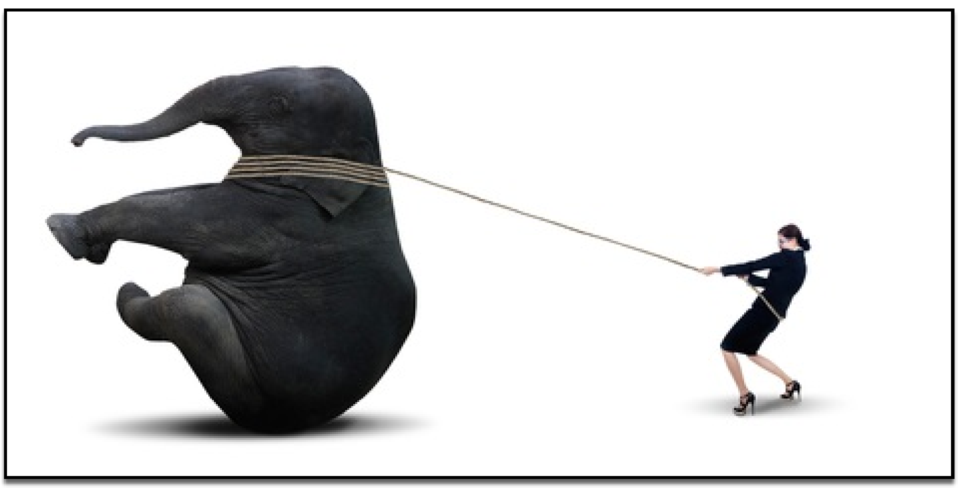
In research, analytics can be used to predict how many casualties might be taken in a given battle using simulations based on past engagements. Marketing analytics can be used to evaluate the recruiting strategies of the Armed Forces and predict candidates most likely to take an interest in military service. Human resources can use analytics to predict how many soldiers will be deploying or returning at any given time and can predict how many will need the help of the U.S. Department of Veterans Affairs or other services.

Finally, consider supply chain management. Quantitative analysis of missions can determine how many rations (MREs) will be needed, how much equipment, how many weapons and soldiers. Without quantitative analytics, these decisions would not be informed by hard data, and thus would have a greater chance of failure.

1.05 Big Data

Big Data

As mentioned earlier in this course, big data refers to very large amounts of data. Before the advent of the modern computer and the Internet, data was calculated in a small-scale, piecemeal fashion. Computing power available to many companies today allows us to create, maintain, and analyze huge amounts of data, although often with the help of data analysts and sophisticated data management techniques.



Companies are gathering data in many forms:

- TV ratings
- browser search history
- learner test outcomes
- user satisfaction surveys
- buying patterns
- social media habits

As technology improves and data collection becomes even easier, we will continue to see the quantity of raw data increase. Parsing through these numbers, analyzing the data, and making informed decisions based on the results, all components of "big data," will continue to drive managerial decision making.

Big data have fundamentally changed the way data is handled and analyzed, allowing significant new patterns and connections to be discovered. Jonathan Shaw, a journalist, has written: "Data, in the final analysis, are evidence. The forward edge of science, whether it drives a business or marketing decision, provides an insight into Renaissance painting, or leads to a medical breakthrough, is increasingly being driven by quantities of information that humans can understand only with the help of math and machines. Those who possess the skills to parse this ever-growing trove of information sense that they are making history in many realms of inquiry."

Big Data can be used to encourage buying behavior. Many websites that provide entertainment make recommendations for their users. They do so by matching your viewing or listening behavior to similar videos or songs (determined by year released, singer, director, genre, rating, etc. and by the historical behavior of other listeners and viewers.) The more you provide feedback for what you liked listening to or viewing, the more information the website has about your preferences. This allows the site to recommend things you might like in the future.

There are ethical and social issues involved with Big Data. In the following article from NPR, Adam Frank discusses the dangers of misuse of Big Data.

Data Mining

Data mining is the process of discovering patterns in large data sets. Data mining is performed on big data to decipher patterns from these large databases.

Data mining has its challenges, which can be exacerbated with an increase in scale. Although large sample sizes are beneficial for statistical analyses, ironically one of the problems with big data is that there is too much of it. Being able to parse relevant data and differentiate between causation and correlation becomes nearly impossible as the databases become huge.

Data mining will often find trends but overlook what the underlying causes might be. With all of its uses and potential problems, big data is growing. People who have the skills to disseminate the massive amount of information that arises from databases have a distinct advantage in today's data-driven world.

Example

The majority of worldwide online searches are conducted on Google's search engine. As such, Google encounters a huge amount of data on a daily basis. If a Google email customer is sent an e-mail about skiing, that user will likely see a banner advertisement offering a deal on skis or lift tickets. This advertising strategy, and thus Google's revenue, is all driven by the use of big data.

Every search performed on Google's search engine, every e-mail sent through Gmail, and every travel route mapped out on Google Maps contains valuable data that Google can use. These services are provided free to the user by Google, but they are costly to create and operate. How can Google afford to operate these services while still being a highly profitable company?

The majority of Google's revenue is generated through targeted advertising, which is most effective when you have data to mine. Studying information about consumer behavior, generated by this big data, gives Google valuable information about what actions and transactions will predict future trends.

The Value of Big Data

The McKinsey Global Institute published "Big data: The next frontier for innovation, competition, and productivity," a report which outlined five broad ways in which big data creates value. These five ways are:

1. Big data makes "information transparent and usable at a much higher frequency."
2. It allows the collection of "more accurate and detailed performance information on everything from product inventories to sick days," thereby exposing variability and boosting performance.
3. It permits the development of more tailored products or services by allowing narrow segmentation of customers.
4. It facilitates analytics that can improve management decisions.
5. It helps the development of next generation products and services through data analysis.

1.06 Video: The Importance of Analytics

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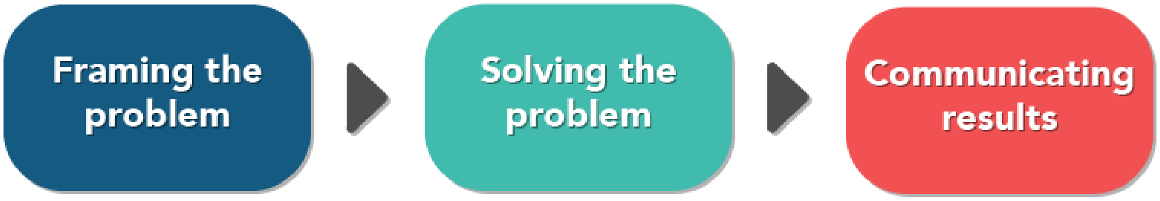
1.07 Models of Quantitative Decision Making: Davenport-Kim Three-stage Model

Models of Quantitative Decision Making: Davenport-Kim Three-stage Model

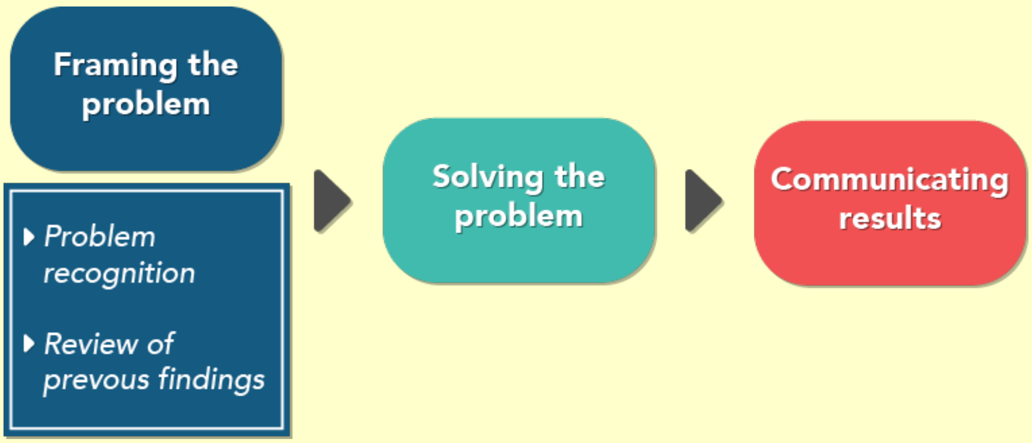
Successful data analytics must start with the issues. Once an item calling for a response is identified within an organization, one can begin to think—often in collaboration with other managers and researchers—about the kinds of research questions and data that might help to address that issue. With the relevant question in mind, the research is guided rather than rambling.

The Davenport-Kim three-stage model was developed by Professors Thomas Davenport and Jinho Kim and can help guide focused issues-based analyses. The Davenport-Kim model consists of framing the problem, solving the problem, and communicating results.



Stage 1: Framing the problem

Framing the problem is further broken down into problem recognition and a review of previous findings.



Problem recognition consists of the following steps:

1	Identifying stakeholders	It is important that the people to whom you're reporting your results are committed to the project and see the need for the analysis.
2	Focusing on decisions	Asking what decisions will be made as a result of the analysis is important for three reasons: it helps to identify the reason for the analysis, it helps to identify key stakeholders, and it helps determine whether the analysis is worth doing.
3	Identifying the kind of story you're going to tell	Although you will be crafting your story in stage three (communicating results), you should begin to think about your audience and what kind of story you want to tell with the data.
4	Determining the scope of the problem	It is important not to get too specific about your experiment at this point, lest you miss an important avenue of investigation.
5	Getting specific about what you're trying to find out	After reviewing the big picture, focus on a narrow set of data that you will analyze.

A review of previous findings can help you to structure your analysis and give you ideas for telling your story when the analysis is complete.

Stage 2: Solving the problem

Solving the problem is the next stage in the model and is where the mathematical "heavy lifting" takes place. The problem-solving stage consists of three steps:

1	The modeling step	A model is a simplified representation meant to solve a particular problem. For example, a company that is trying to maximize its targeted advertising may create a model. This model could study sales by different age demographics of consumers. Here, sales and age would be the two variables involved in the model; the features being tested are the company's sales and the age of its consumers.
2	The data collection step	This is the part of the project where data is gathered either from primary or secondary sources and then measured. It is important to recognize the difference between structured and unstructured data. Structured data is data in a numeric form that can be easily put into rows and columns. Unstructured data has become more prevalent in recent years and consists of things like text, images, and clickstreams. These things will need to be quantified before analysis can be performed.
3	The data analysis step	The goal of data analysis is to find patterns in the data that can then be explained using more sophisticated statistical techniques. The level of analysis will depend on the type of story you want to tell. Remember, from the first stage that there are different ways to tell a story. These will be discussed more in the next stage.

Stage 3: Communicating results

Communicating and acting on results is the last stage in the three-stage model. While you may think this is the least important part of the process, it is essential if you want your findings to result in action. We'll consider this important stage of the process later in the module.

1.08 Levels of Measurement

Levels of Measurement

Continuous and Discrete Data

Data is sometimes referred to as either continuous or discrete. With continuous data, a data point can lay along any point in a range of data. An example of continuous data might be age. It is possible to be 22.67 years old. Discrete data can only take on whole values and has clear boundaries. It is not possible to own 3.4 cars; you either own three cars or four. These are discrete data points.

Nominal data

Nominal data, sometimes called categorical data, is used to label subjects in a study. Nominal data is a type of **discrete** data. This measurement places an object into a category, rather than attaching some quality to them. If you were to code males as 0 and females as 1 in an analysis, this would be an example of using nominal data.

Ordinal data

Ordinal data is a type of **discrete** data. It places data objects into an order according to some quality. So, the higher a data object on the scale, the more it has of a certain quality. For example, a third-degree black belt is presumed to have more expertise in karate than a first-degree black belt. Ordinal data allows you to place objects in some kind of order.

Interval data

Interval data is a type of **continuous** data. It has an order to it, and all the objects are an equal interval apart, so in interval data the difference between two values is meaningful. You cannot have a natural zero point in interval data, and zero does not represent the absence of the property being measured.

Time and dates, as well as temperature, can be measured using interval data. For instance, the time of day is measured using interval data. Each minute during the day is an equal, meaningful interval apart. It has an arbitrary zero, at midnight, or midnight and noon, that does not represent the absence of time. Another example of interval data is temperature. The difference between each degree is equal and meaningful, and zero degrees Fahrenheit does not signify the absence of temperature. These are two of the few examples of interval data, which is not very common aside from measuring temperature and time.

Ratio data

Ratio data is a type of **continuous** data, like interval data. Unlike interval data, ratio data has a unique zero point. With ratio data, numbers can be compared as multiples of one another. One example of ratio data is age. Someone can be twice as old as another person, and it is possible to be zero years old. If you were to compare the Fahrenheit and Kelvin temperature scales, you would find that the Fahrenheit scale is not ratio data, but the Kelvin scale is ratio data. This is because zero degrees Fahrenheit has a corresponding non-zero value on the Celsius and Kelvin scales and is therefore not unique. The Kelvin scale, however, has a unique zero value called absolute zero, making it ratio data.

In business, ratio data is common. For example, income, stock price, amount of inventory, and the number of repeat customers are all examples of ratio data. These each have a unique zero point and can data within each of these groups can be compared through multiplication. You may notice that monetary amounts fit this description. In fact, when studying a monetary amount, ratio data is used as a natural zero exists at $0, and $100 is clearly twice the amount of money as $50. If we were to model the income of various CEOs, we would be using ratio data.

1.09 Reliability and Validity of Data

Reliability and Validity of Data

In statistics (as well as science) measurements need to be both reliable and valid. Reliable data is both consistent and repeatable. If you were to administer the same test to the same person three times and the scores were similar each time, the test could be categorized as reliable. If the results varied greatly, the test would be unreliable. Similarly, valid data is data resulting from a test that accurately measures what it is intended to measure. For instance, if a test reflects an accurate measurement of a student's abilities, it is said to be valid.

Errors: Random versus systematic

All measurements contain some degree of error. This error may be random or systematic. Random errors should cancel themselves out over a large number of measurements if they are NOT related to the true score and if there is no correlation between the errors. If the errors do not meet these criteria, they are not random. Systematic errors are not due to chance, and although they can be corrected, correcting them takes time and attention to detail. Systematic errors are more difficult to find because the data is likely consistently askew in the same direction. Skewness is a measure of the degree to which data "leans" toward one side. If data is collected using an instrument that needs calibration, this error will repeat itself consistently across the data set.

Measurement bias

Measurement bias can invalidate the results of any study, so it is important not to let bias creep into your experiment. Because it is usually impossible to measure results for an entire population, a sample of the population is measured. To produce unbiased results the sample tested must be sufficiently random. If, for example, you ask 100 people in Annapolis, MD whether they prefer the Army or Navy, your sample is likely to be biased in favor of the Navy because the U.S. Naval Academy is located there. A better methodology would be to randomize your sample and get opinions from people in many locations throughout the country.

Information bias

Assuming your sample is properly randomized, the second way bias can enter your model is when data is collected. This is called information bias and may occur for a variety of reasons. Your interviewer might be biased and may ask questions in a way designed to elicit a certain response. The questions themselves may be biased in favor of a certain outcome, or a responder may lie in their responses. The best way to combat information bias is to keep both interviewers and responders in the dark about the purpose of the survey, inasmuch as this is possible.

For example, consider a transit authority trying to determine whether a new passenger rail line from Big City to Springfield would draw a sufficient ridership. As a way of assessing demand, it interviews people in Springfield employing the following interview questions:

- "Would you be willing to ride a new, affordable train on your next trip to Big City if the service existed?"
- "Are you in favor of limited train service into Big City if it involves lengthy disruptive and costly construction?"

Notice the likely responses to each question. While many people might answer "yes" to the first question, many of those same people might answer "no" to the second question. The results of either survey would include informational bias.

For Reflection

1.10 Video: Concepts of Measurement

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1.11 Data Management

Data Management

Data management refers to cleaning and organizing a data set that has been collected. Most of the actual data you receive is not ready to be analyzed. Data management is a vital step in the decision-making process, and good data-driven decisions rely on clean data.

Because humans are involved in collecting and inputting the data, errors will happen. In "What We Know About Spreadsheet Errors," Raymond Panko argues that "when humans do simple mechanical tasks, such as typing, they make undetected errors in about 0.5% of all actions. When they do more complex logical activities, such as writing programs, the error rate rises to about 5%."

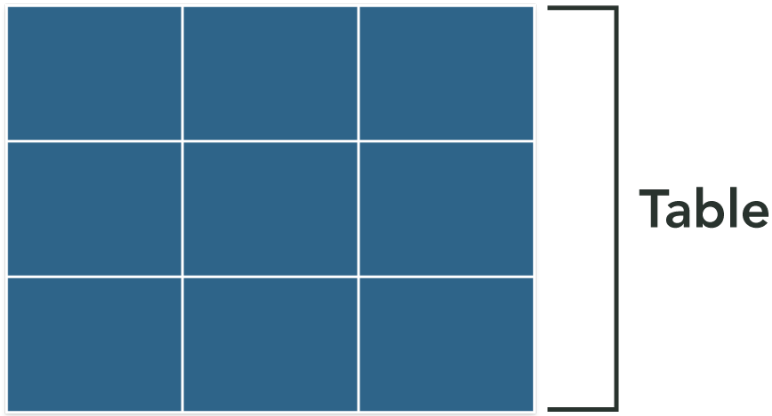
There are other potential sources of error. The data entry person may have missed a row when entering the information, and all subsequent rows may be one row off. The software used to enter the data may not be compatible with the software you're using to analyze the data and may not translate correctly.

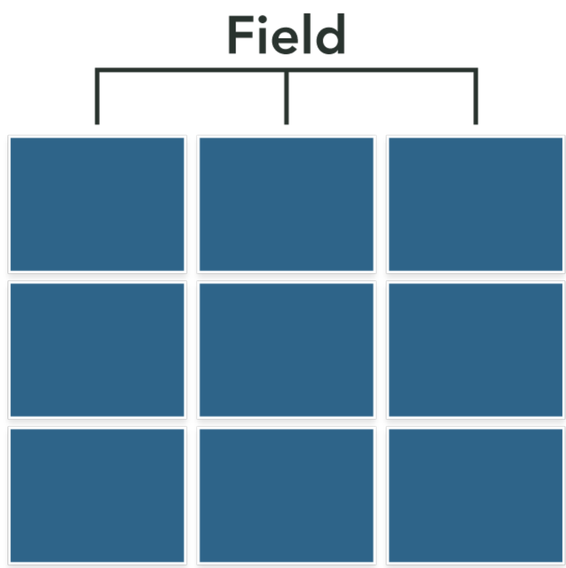
The best way to avoid data mistakes is to spend time checking it, checking it again, and then checking it one last time. Time spent checking the data is time you won't have to spend reanalyzing the data. Another safeguard against data errors is setting up a hierarchical reporting structure in which each person is responsible for different aspects of the data management process. This makes it far easier to determine where something might have gone wrong and how to resolve the issue.

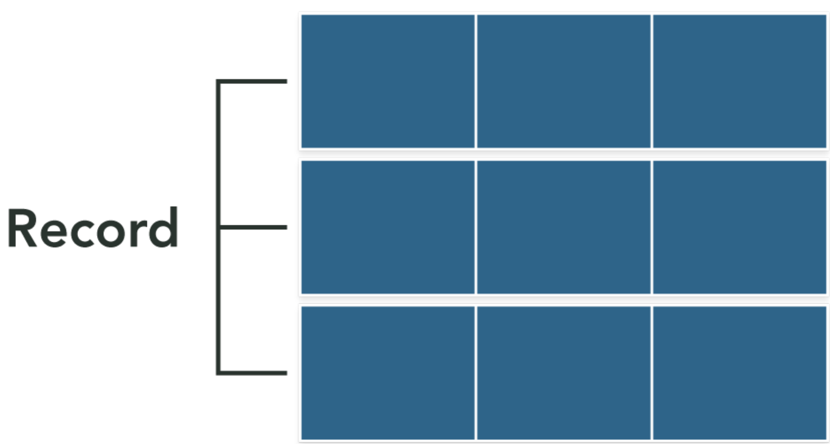
Spreadsheets or Relational Databases

After collection, your data should be entered into a spreadsheet program or relational database. Spreadsheets and databases make it easier to port into and between statistical software packages such as SPSS, SAS, and R.

In general, fields contain information about one part of each subject or object in the sample. For example, the subject's name, phone number, and age are fields. Fields are typically represented by columns. A record contains all of the data for a particular subject or object in the sample. For example, a record will contain all of the collected data for subject A. Records are typically represented by rows.







Spreadsheets and relational databases also make it easier for you to check your data for any missing or out-of-range data because the data is neatly organized into rows and columns. These types of files have come to be known as rectangular data files, and they are the preferred method of storing data.

Missing Data

Missing data (an omission error) is a very serious data error. Omission errors occur when something, such as crucial data, is missing. The missing data may be intentional, unintentional, or even a fault of the study. For example, consider a city government is trying to determine the national origins of its recent immigrant population. If a survey is conducted in English, people from non-English speaking countries may not respond to the survey, causing that group to be underrepresented. Because of this missing data, the results of the study may be skewed. In general, missing data tends to skew the results of the analysis.

1.12 Data Quality

Data Quality

Starting with accurate data will give you reliable results when that data has been analyzed. Starting with flawed data will produce questionable analyses. In the parlance of computer programmers, this is known as the GIGO (Garbage In, Garbage Out) principle. In some cases, you may spend more time managing data than analyzing it.

When looking at data, it is productive to look for outliers, observation points (numbers) that are distant from other observations. When outliers are detected, we can examine our study techniques and determine whether the number is incorrect and/or can be converted to a correct number. We can also determine whether a figure is an outlier because it describes something that does not belong in the study. An outlier may even be correct, but it is helpful to identify any outliers and determine whether they should be used.

The best fix for faulty data is often to check your work carefully. Having someone else with a set of well-trained eyes examine the results and processes of a study can help identify any problems with the statistics. While it is tough to predict in which specific way a study may yield faulty results, constantly checking your work throughout can help ensure a high level of data quality.

1.13 Video: Data Quality

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1.14 Video: The Uses of Research

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1.15 Research Design

Research Design

The two main types of research design are observational studies and experimental studies.

Observational Studies

Observational studies are also known as quasi-experimental studies. An observational study is sometimes used because it is impractical or impossible to control the conditions of the study. Mystery shopping is an example of an observational study that is employed in the retail industry. The "mystery shopper," whose identity is unknown to the staff of a retail store, will shop or perform other tasks, and report the results. If the staff of the store knew about the study, their behavior would undoubtedly change. Therefore, it is impossible to control the conditions being studied, necessitating an observational study. The best kinds of observational studies are forward-looking, or prospective, and focus on a random group, or cohort.

A prospective cohort study observes people going forward in time from the time of their entry into the study.

While observational studies are generally considered weaker in terms of statistical inference, they have one important characteristic: response variables can often be observed within the natural environment, giving the sense that what is being observed hasn't been artificially constrained.

Experimental Studies

In an experimental study all variable measurements and manipulations are under the researcher's control, including the subjects or participants. For example, when studying the impact of price changes on consumers, a researcher can manipulate the price of the product. In such a study, the researcher can control all elements.

There are three elements to an experimental study:

experimental units	subjects or objects under observation
treatments	the procedures applied to each subject
responses	the effects of the experimental treatments

Below are the steps to setting up a statistical experiment:

1. Identify the experimental units from which you want to measure something

   The set of subjects is a sample or a smaller representation of an entire population. A population refers to the entire pool of people. For example, if you measure a presidential candidates' support among American voters, the population is the entire pool of American voters: all registered voters in the United States. Because of the difficulty and impracticality of studying an entire population, a representative sample is studied instead.

   Your sample should be chosen at random, in order to ensure that your results describe the population at large. Choosing a sample from a homogeneous group can skew your results. For a sample to be truly random, the selection of any particular subject or participant must be independent of the selection of any others.

2. Identify the treatments that you want to administer and the controls that you will use if you will use a control group

   A treatment is a procedure or manipulation to which you want to expose the subjects to achieve an experimental result. In every experiment, there is a treatment group and a control group. A control group is a sample group that is not subjected to the treatment. This will help to determine whether those who received the treatment are actually responding to it when compared with the results of the control group.

3. Generate a testable hypothesis

   You then generate a testable hypothesis about how the response variable will be affected, run the experiment, and analyze the results.

Validity

As we have seen previously, valid data accurately measures what it is intended to measure. Because valid data is not found by coincidence, those studies that yield valid data can often be repeated many times by different researchers with similar results achieved each time.

There are four main types of validity: construct validity, content validity, internal validity, and statistical validity.

When you take an abstract concept and make it a quantifiable variable, or operationalize it, you create a construct. Construct validity means that the construct has been generally accepted in the field. Closely related to this is content validity, which refers to whether the construct measures what it claims to measure. Content validity may be questioned if the construct is too wide or too narrow. Internal validity concerns biases that may find their way into the data that is collected. These may be systematic biases, intentional biases, or self-serving biases. Any of these may lead to questions about your study's internal validity. Finally, there is statistical validity: do your results stand up to statistical scrutiny? This can be validated through the use of hypothesis testing, which will be discussed later in this course.

Bias

Assuming you have followed good statistical methodology, you have chosen a completely random sample, and you have designed a study that minimizes systematic errors. Other influences can introduce bias into your experiment, however. Let's look at another drug trial to find out how bias can enter an experiment.

In drug trials, there are generally three populations: the treatment allocator, the participant, and the response gatherer (sometimes the treatment allocator and the response gatherer are the same person). Any or all of these populations can introduce bias into the study if they know who is in the control group and who is in the treatment group. The need to keep participants in the dark about this is self-evident, but subtle attitude changes in the treatment allocator and response gatherer may also affect the study results. To eliminate this bias, designers of the study may decide to have a blind, double-blind, or triple-blind study.

In a blind study the participants are not told if they are in the treatment group or control group. This is very common in drug trials to prevent the participants' mental states from biasing the effects. For example, the placebo effect occurs when a participant in the control group begins to show the effects of treatment because they believe they are in the treatment group. In a double-blind study neither the treatment allocator nor the participant knows in which group the participant is contributing. In a triple-blind study the response gatherer also does not know. This study design completely eliminates any bias on the part of anyone involved in the study.

1.16 Video: Research Standards

This assignment does not contain any printable content.

1.17 Vocabulary Game

This assignment does not contain any printable content.

1.18 Flashcards: Module One

Flashcards: Module One

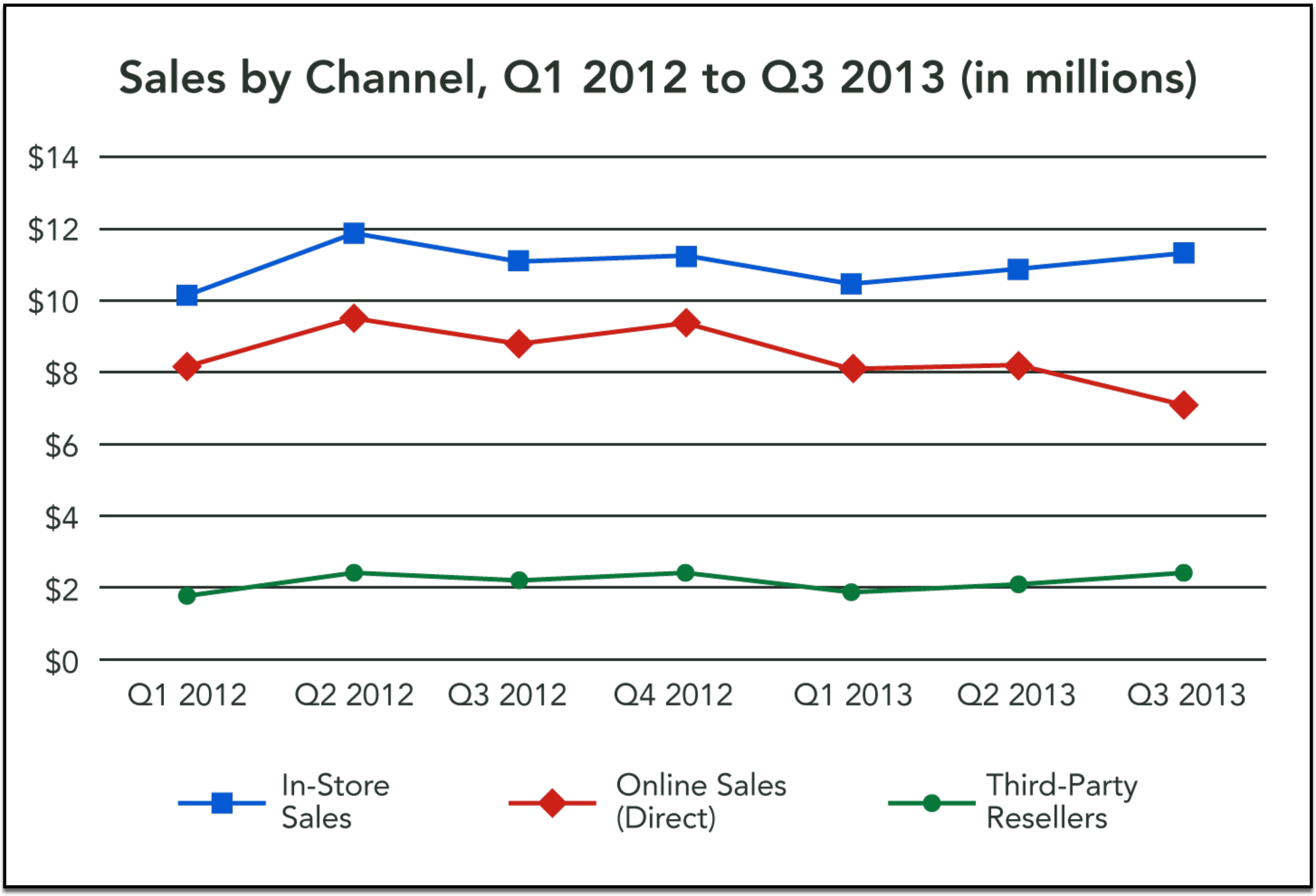
Term	Definition

1.19 Case Study: Aligning Sales Objectives with Email Marketing Campaigns

Case Study: Aligning Sales Objectives with Email Marketing Campaigns

Anil Patel stares at the screen of his computer, contemplating the latest challenge facing him and his team of email marketers at ComfyTech Footwear, an online retailer of high-end outdoor shoes. ComfyTech has an enthusiastic following among hikers, many of whom purchase directly from the company's website. ComfyTech now generates 40% of its sales through web purchases, making email and web-based marketing a key component of the company's sales strategy.

In a sales department meeting earlier that day, Patel and his colleagues reviewed data showing a significant decline in online sales revenue, resulting in his team missing their target for the previous quarter (Q3 20X1). Furthermore, online sales for this period were down 19% from the same quarter a year ago.



Patel was surprised by these results, especially since his latest email marketing campaigns had been very successful, achieving impressive response rates and increased visits to the ComfyTech website. In addition, he and his team of web designers and campaign strategists had optimized the website experience to make it easier to navigate. They had purchased banner ads on third party sites to promote ComfyTech products and increase site traffic. They had even run email marketing tests to compare the effectiveness of different email subject lines on click-through rates to the site.

Patel has been in the marketing business for a long time, and his experience has repeatedly validated his belief that consumers are attracted to discounts. Therefore, it was no surprise when his team's test of different email subject lines yielded a much higher response rate for the subject line that clearly articulated a substantial discount offer.

Test Group	Email Subject Line Message	Open Rate (Emails opened/emails delivered)	Click Through rate (clicks to website/ emails delivered)	Average # of minutes spent on site after clicking	Conversions (Purchases/ emails delivered)
1	"Step into our new fall collection"	17.9%	13.7%	4.9	1.2%
2	"Save on fall footwear basics" (control group)	18.1%	13.9%	3.75	1.5%
3	"Get up to 40% off selected items"	21.2%	15.5%	5.25	2.5%

Sitting in his office after the sales meeting, Patel mulls these results and is puzzled by the drop in sales that seemed to coincide with such promising email campaign metrics. His campaign data shows that more email recipients are clicking on the site, spending more time on the site and even making more purchases. His screen saver flashes images of enthusiastic ComfyTech customers trekking through the woods. What new strategy his team pursue to improve the site's performance, and by extension, online sales volume?

He jots down three possible next steps for his team to consider:

1. Purchase more paid banner ads on third-party sites to drive more people to the site and hopefully increase purchase volume.
2. Focus on redesigning the site's call to action buttons ("purchase now") next to key products to get more site visitors to make purchases. Use these call to action buttons as an opportunity to reiterate discount offers.
3. Test email response rates for messages sent on different days of the week to look for opportunities to boost click-throughs and purchases.

Patel meets with his team to review these three strategies and get their feedback as well as any other ideas. Cameron Logue, one of the newer campaign managers, hesitantly suggests that they ought to consider reducing the emphasis on discount offers. She says her gut tells her that they may be attracting the wrong kind of customers who spend less and rarely return for repeat purchases, preferring to shop around for big discounts. Most of the team members dismissed this notion, based on the overwhelming "Subject Line Test" results. "Look at how much we increased our click-through rates when we promoted discount offers," Patel says. "Clearly it doesn't make any sense to run a campaign that attracts fewer eyeballs."

In spite of his remarks, Patel realizes there could be some merit to Logue's suggestion. Perhaps their previous tests had been flawed. If so, it might make sense to review additional data from the test to see if the customers who clicked through from Test Group 1 (the subject line with no discount offer) actually spent more, on average, than those from Test Group 3, who responded to the "up to 40% off" emails.

He walks over to the cubicle of Dirk Bangert, the company's Database Manager, to ask him to pull additional transactional data from the three test groups that received the emails with the different subject lines. He was certain that Bangert could help him analyze the right data to determine if those customers that weren't solely lured by discounts would be willing to pay more, through higher spending and repeat visits. If so, this could be the key to reversing the decline in sales. He has to be sure he looks at the most important metrics this time.

Review Checkpoint

Answer the following question in the textbox, then click *Save* to compare your answer to an answer written by an experienced practitioner.

Question 1. What is the key flaw in Patel's conclusions about the team's Subject Line test, and what would have been a more relevant item to measure and compare for each group?

Question 2. Why is Patel's first idea (purchasing more banner ads on third party sites to drive increased site traffic) not likely to help achieve his team's goal?

Question 3. Do you think Logue's gut instinct to rein in email campaigns promoting discount offers is a good idea? Why or why not?

Question 4. If Patel and his team can identify a segment of loyal customers that values the product's features and benefits, as well as another segment of customers that only respond to discount offers, do you think they should send

different email offers to each of the segments? What are some examples of those different offers? There is no right answer here; try to be creative.

Suggested/Sample Responses

Question 1:

The "Email Subject Line" test measured the increase (lift) in response rates, including the percent of recipients that opened the email, the percent that clicked through to the website, the average time spent browsing on the site, and the percent of recipients that made a purchase. These metrics made it look as though the email highlighting the discount offer was more effective, which it was in terms of driving traffic. But these results did not reveal which group spent the most on purchases after receiving the email, which would have been more aligned with the company's high-level goals.

In others words, Patel needs to consider how the conversion rate (number of purchases per emails delivered) translates into return on investment (ROI). In this example, one offer converts at 2.5% and the other at 1%, so it's a valid assumption that the 2.5% conversion is the better performer. If, however, you look at the average order value for the offers, you may see that the one converting at 2.5% is only $50, while the one converting at 1% is $250. Now the 1% conversion has the higher ROI and is really the best measure of the success of the campaign.

Question 2:

Patel's team has tried this approach in the past, and while it has probably generated new visits to the ComfyTech website, there is no evidence to suggest that this has helped increase the sales volume through the site. If Patel was to pursue this approach in the future, he should do a careful test using web analytics to make sure that the total amount of sales revenue generated from customers who clicked on banner ads is greater than the total amount spent on the banner ad campaign (whether measured as cost per click or cost per conversion). This "Return on Investment" analysis will help him determine if the campaign is producing valuable leads that not only click the banner to visit the site but also are likely to purchase specific products or spend a particular amount.

Question 3:

Logue's suggestion is certainly worth investigating. It would make sense that, although "discount-oriented" consumers will be inclined to check out a compelling offer (as will many consumers), they may be less enthusiastic about the products than core ComfyTech customers who are more interested in the features and benefits of the product than the price. It is plausible that these loyal customers will purchase more shoes, more frequently, and will often be willing to pay full price. Even if fewer recipients click through the "non-discount offer" email and browse the site, those who do may be more likely to spend more. Patel's team should test this theory, either by examining recent purchase history for recipients in the three Subject Line Test Groups and comparing spend or by creating a new test.

Question 4:

Yes, if you know enough about your distinct customer segments, it makes sense to appeal to them with customized offers that meet their needs and desires. It is important, however, to continuously measure the results of these offers and to ensure that campaigns are profitable.

1. For the loyal customer segment:
    a. Promote opportunities to preview new styles and get first preference on size and colors.
    b. Encourage customers to send in photos of places they've hiked with their shoes to get a chance to be featured on the site and/or win free merchandise
2. For the discount-oriented customer segment:
    a. Promote offers on last season's styles or excess inventory
    b. Use discount offers to reward desired behavior (e.g. second pair at half price)

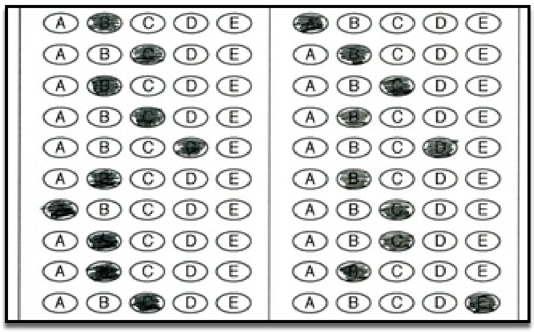
1.20 Case Study: Data-Driven Decision Making in a Suburban School District

Case Study: Data-Driven Decision Making in a Suburban School District

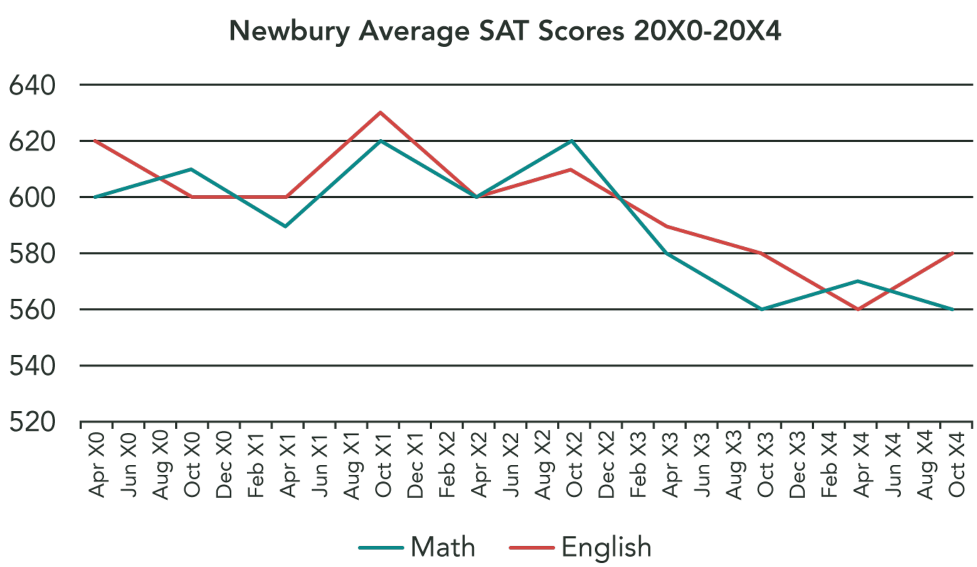
Linda Jones is the superintendent of schools for the Newbury Public Schools, a small K-12 district in an affluent suburb of Boston. She has served in her position for two years after a four-year tenure as an elementary school principal in the District. The Newbury Schools have a strong academic reputation, based on high standardized test rankings and Advanced Placement testing performance. Parents tend to be involved in the schools and are frequently vocal in expressing their opinions about school policies, educational direction, and teacher effectiveness.

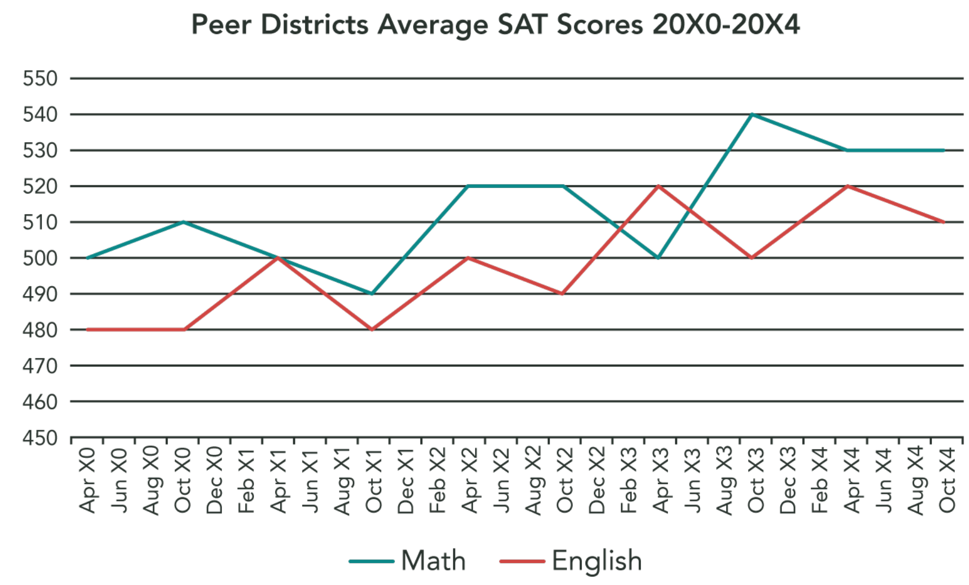
In spite of the many positive academic trends at the Newbury Schools, Jones has just received a report detailing the SAT results for the 520 district students that took the latest test. These results show a continued decline in test scores that began over a year ago and has sparked concern among parents and administrators. Jones needs to prepare for a discussion of these results at an upcoming school committee meeting, and she has already heard that a group of particularly strident parents will attend. One of these parents has theorized that declining math results can be attributed to the retirement of two veteran math teachers and the ineffectiveness of the newer teachers who replaced them. She has surveyed a handful of friends whose children had the retired teachers, and almost all of them had received high math SAT scores, while those whose children had the newer teachers received disappointing scores. While there is a growing cohort of parents putting pressure on Jones to deal with the new math teachers, she has no evidence to believe they are any less effective than their predecessors. Unfortunately, she cannot yet explain why the results have been declining or what she can do to reverse the troubling trend.

Jones realizes that her first step is to collect appropriate data to gain a deeper understanding of the problem. In recent years, Newbury, like all districts in the state, has amassed a vast array of student information, including demographic data, MCAS results by student subgroups, formative assessment results, teacher evaluations, class sizes and much more. Her challenge is to determine which of this data will help her understand the declining scores and provide quantitative evidence for an effective strategy to improve them going forward. This study will be especially important if financial resources are necessary to implement the strategy.



She begins by asking her assistant, Mary Schmidt, to prepare a chart of the District's SAT data, compared with peer districts' SAT scores, from the past ten testing sessions. Later that afternoon, Schmidt gives her the following charts to review:





While reviewing this high-level data, Jones focuses on the palpable decline that began with the April 20X3 test scores, about six months after she assumed the role of superintendent. She knows that there were many changes that took place around that time, including changes to curriculum, high turnover among teachers and budget decisions that resulted in increased class sizes in many secondary level math and English classes. She also suspects that the economic downturn has forced more families to forego costly, private SAT prep courses and tutors, and she wonders if it would be worthwhile for the district to fund free after-school SAT prep sessions for juniors and seniors to supplement preparation for the test.

Jones realizes she needs to analyze all possible root causes of the problem, in addition to validating her theory about the need for more available SAT prep. She decides to organize a quick online survey of juniors and seniors, as well as graduates who took the SATs in the past five years, to find out percentages of test takers that completed private prep courses, along with qualitative questions about how well prepared they felt. In addition, she asked the district's data administrator to perform a statistical analysis to look for any significant correlations between students' SAT scores and their academic performance, high school math/English teacher assignments, class sizes, formative assessments, and demographic characteristics. This analysis produced no significant insights except for a tendency of boys to score slightly higher in math when they had received several years of instruction in smaller class sizes.

Jones believes strongly that Newbury students can reverse the decline in SAT scores by providing after-school SAT prep sessions as an alternative to costly private courses. The early results of her survey corroborate her assumptions by showing a decline in SAT prep course enrollment in the past two years. She is concerned, however, that she has not done enough to substantiate this link to the district's SAT results. She also knows the School Committee will need to be confident that offering district-funded prep courses will have a high likelihood of improving SAT scores and easing parents' concerns.

Review Checkpoint

Answer the following question in the textbox, then click *Save* to compare your answer to an answer written by an experienced practitioner.

Question 1. Please review the two charts containing SAT score trends for Newbury and peer districts. How would you summarize the problem that Linda Jones is facing with regard to Newbury students' SAT scores?

Question 2. Linda Jones has an untested hypothesis that explains the decline in Newbury students' SAT scores. In addition to surveying families about their use of private SAT prep courses, what other types of data analysis should Jones do to ensure she has considered all possible root causes of the

problem?

Question 3. Do you think Jones' approach to surveying current and past students about their level of private test preparation is an effective way to test her theory and recommended approach? Why or why not? What are some basic survey guidelines she can follow to be sure she gets valid, actionable data? Can you think of anything else she could do to substantiate her theory or find out if offering after-school SAT prep is a good idea?

Question 4. How would you advise Linda Jones to present the problem and her recommendations at the upcoming School Committee meeting?

Suggested/Sample Responses

Question 1:

Newbury is a high performing school district, but students' SAT scores have been showing declines, while comparable districts have shown more consistency over the same time period. Jones needs to identify and analyze available district data to understand what, if any, variables might be contributing to the decline.

Jones has been receiving parent feedback about newer teachers being less effective in preparing students for the SAT, but she is skeptical about this being the problem. She has also heard stakeholders blame curriculum changes, larger class sizes, and increased demographic diversity, and she realizes that she will need to conduct quantitative analysis to either substantiate or dismiss any of these beliefs.

Her personal belief is that declining test scores are due, at least in part, to household budgetary constraints that have led to decreased spending on private SAT prep courses. If data analysis supports this theory, then Jones will feel confident proposing alternative, district-funded SAT prep sessions to help improve scores.

Question 2:

Jones should gather available data on all Newbury students (past and present) that have taken the SAT in the past five years and categorize them according to their scores (e.g., high, medium, low). Within each segment, Jones should look for statistically significant attributes (e.g., large class size, X teacher, overall GPA, etc.) that would predict a particular SAT outcome. Note that this exercise is similar to what the parent did (surveying a group of friends for patterns to find the cause of the poor results), but the difference is that Jones would be doing the analysis on a large sample size of thousands of students. Furthermore, the district's database administrator would likely conduct the analysis using statistical software that automates the process of looking for meaningful correlation.

If the data suggests that a particular factor is a root cause (e.g., large class size), Jones can advocate for smaller class sizes. She could even test this solution on the next SAT test by comparing results of a control group against a "modified" group (results of students in small class sizes vs. those in larger classes).

Question 3:

Assuming that Jones does not already have available data on students' test prep participation, a survey is a reasonable way to gather data. However, she should ensure that she has a valid sample size and adequate response rates. She must also construct her survey to ensure that her questions are clear and do not lead respondents to support her bias.

Jones could also collaborate with other superintendents to see if there are similar results across the state and if any similar proposed SAT courses have been implemented and had positive results.

Finally, it would be helpful to gauge current students' interest in a district-funded SAT prep course, if offered. Jones could gather qualitative and/or quantitative data about whether or not students would be likely to enroll in such a course and believe it would be helpful.

Question 4:

Instead of responding defensively to parents and committee members, Jones should come to the meeting prepared with the results of her data analysis and easy-to-understand charts that clearly dispel the correlation between suggested causes that do not, in fact, have any statistical relation to the declining SAT scores. She should also be prepared to present her survey findings that show the corresponding decline in private SAT test prep courses. This will arm stakeholders with data that tells a more complete story and helps key audiences understand the root causes of the challenges with SAT test scores. This discussion will be an ideal basis for Jones to propose district funding for after-school SAT prep courses that would increase the percentage of students that receive this preparation and, as a result, score higher on the test.

If Jones' data analysis has identified any other possible causes for declining test scores (for example, students who perform poorly on math SATs have tended to show difficulty on certain sections, such as geometry or quadratic equations), attention can be directed to areas that will help students who demonstrate this weakness (for example, additional support or teaching emphasis, etc.).

1.21 Module 1 Printable PDF

This assignment does not contain any printable content.

1.23 Module Feedback

This assignment does not contain any printable content.