1

THE LANGUAGE
OF STATISTICS

What you will learn from this chapter

- How to describe data in a spreadsheet
- How to categorize variables by their scale of measurement
- How to identify whether variables are continuous or discrete, quantitative or qualitative
- How to identify a Likert-type scale
- How to specify a population and produce a sample from it
- How to identify constructs of interest and operationalize them
- How to identify experiments, quasi-experiments and correlational studies

Data skills you will master from this chapter

- Creating a dataset
- Identifying a dataset
- Navigating a dataset
- Specifying variable characteristics (SPSS only)

CASE STUDY

WHAT DO I DO WITH THIS SPREADSHEET?

Ben is the owner of Scoops, a local frozen yogurt chain with five locations. Sales have been slumping at some of these locations, and Ben wants to determine the cause. He suspects that some of his store managers have been letting customer satisfaction slip, but he needs a stronger case than a gut feeling to convince them to change their ways. He decides that the first step in getting this evidence will be to assess customer satisfaction at each location and see if it’s affecting sales.

Because Ben doesn’t have a background in statistics, he runs a search on the Internet for a consultancy that can help him answer his questions. He contacts one of the results from his search, Surveys 1-2-3, because they promise to use ‘data-driven techniques to answer any question you have about your business’ for a reasonable fee.

(Continued)
CHAPTER 1

Although for-profit organizations have always focused on the bottom line, there is increasing pressure to collect data from all areas of the organization in order to stay competitive. Simply producing a good product or delivering excellent customer service is often not enough; the owners of a competitive business must constantly conduct research on their own organizations to identify weak points and repair them.

As a result, the case study described above is common in growing small businesses. Suddenly finding themselves needing to conduct such research, many small business owners simply do not have the skills to do so. Like Ben, many recognize this need but do not even fully understand the results of research conducted on their behalf. Learning statistics and research methods are the keys to preventing this from happening to you.

In this chapter, you will take the first step toward understanding statistics: learning the language of statistics. This is an especially important chapter because everything else you’ll learn about statistics builds on these concepts. So take your time and make sure you understand them completely before moving on to the next chapter.

1.1 Describing Numbers

In the first half of this chapter, we’ll explore ways to talk about numbers in spreadsheets.

1.1.1 Datum, Data and Datasets

The general term for a single value collected in the context of research is a datum. A datum might be a number, letter or word. For example, a ‘2’ is a datum, but so is ‘yellow’ or ‘tall’ or even a ‘p’. When you are referring to more than one datum, you are referring to data. You might say, ‘take a look at this datum’ or ‘these data are interesting’.

When related data are collected in one place, a dataset is created. In our case study example, the spreadsheet that Ben received was a dataset, as it contained a great deal of data collected for a single purpose. A small piece of that dataset might have looked something like Figure 1.01.

We would refer to this spreadsheet as a dataset, which contains many data. In the Q2 column in Figure 1.01, the first ‘3’ is a datum, but if we referred to both that 3 and the 3s below it, we are talking about data.

Datasets can be further described with two other terms appearing in Figure 1.01: cases and variables. A variable is a collection of data with different values based upon its source,
represented in a dataset as a column. For example, if you measured your height and the height of all of your friends, you have measured height as a variable. In Figure 1.01, Store, Q1, Q2 and Q3 are all variables.

If you remember anything from secondary/high school algebra and geometry, you probably remember the value called pi. This value is equal to 3.14159..., with infinitely more numbers after the decimal. Pi is always this value. It never changes. Any time you see the word ‘pi’ or the symbol π, you know this is what it means. That is what makes pi a constant. If a value is not constant – or in other words, if it varies – it is a variable. When you see the word ‘height’, it could refer to your height, your friend’s height, the height of a building, or any height at all. That means height is a variable. In statistics, constants are generally used in formulas, and variables are usually parts of datasets.

So now that we have all these variables, how do we know where the data came from? A case is an independent source of data about one or more variables, represented in a dataset as a complete row. In Figure 1.01, Case 1 contains four data: an ‘A’ for the Store variable, a ‘2’ for the Q1 variable, a ‘5’ for the Q2 variable and a ‘yes’ for the Q3 variable.

In summary, a dataset is a collection of data linked together in some meaningful way. A dataset is a spreadsheet containing variables as columns and cases as rows. Each variable represents a collection of a single type of data, while a case represents all of the data on all variables in the dataset from a single source.

### 1.1.2 Scales of Measurement

Once we have a dataset, we need terms to describe the kinds of data we’re looking at. This is important because different kinds of data call for different kinds of analyzes (more on this in later chapters). So, what really is the difference between a ‘3’ and a ‘yes’?

The most basic categorization of data is quantitative versus qualitative data. Quantitative data are quantities (usually represented as numbers), while qualitative data are labels or qualities (usually represented as words or letters). In our case study dataset, Q3 is clearly qualitative because ‘yes’ and ‘no’ are labels. Q1 and Q2 are probably quantitative because they are represented by numbers.

You might have noticed the word ‘probably’ in my previous sentence. This is where things get a little tricky! Some numbers are quantitative and others are qualitative. The difference is driven by what those numbers represent.
For example, consider the number on a footballer’s shirt. This number is not a quantity because higher numbers do not represent ‘more’ of anything. A player with a 12 is not necessarily more skilled, more respected or even taller than a player with a 5. If ‘shirt number’ were a variable in a dataset, it would be a qualitative variable.

Another way to conceptualize data is by considering scale of measurement. There are four scales of measurement: nominal, ordinal, interval and ratio. Each in this order is more specific (has more requirements) than the one before – see Figure 1.03. For example, all ordinal scales can also be considered nominal scales, but only some ordinal scales are also interval. To illustrate the differences between these categories, we’ll cover each scale of measurement in turn, considering the following four variables as we go, each with three cases:

1. **Opinions from focus groups**: ‘I liked it’, ‘I’m not sure if I liked it’, ‘I didn’t see it’
2. **Ranked product preferences**: 1st, 2nd, 3rd
3. **Employment test ranging from 10 to 30**: 10, 20, 30
4. **Sales in euros**: 10000€ per year, 20000€ per year, 30000€ per year

**FIGURE 1.02**
Examples of quantitative and qualitative data

<table>
<thead>
<tr>
<th>Quantitative</th>
<th>Qualitative</th>
</tr>
</thead>
<tbody>
<tr>
<td>numeric survey responses (1, 2, 3, 4, 5)</td>
<td>opinions from focus groups (&quot;I liked it&quot;)</td>
</tr>
<tr>
<td>sales in euros (10000€ per year)</td>
<td>product preferences (&quot;Version A&quot;, &quot;Version B&quot;)</td>
</tr>
<tr>
<td>turnover rate (25 employees per year)</td>
<td>rankings (&quot;1st&quot;, &quot;2nd&quot;, &quot;3rd&quot;)</td>
</tr>
<tr>
<td>counts (2000 Twitter followers)</td>
<td>verbal approximations (&quot;high&quot;, &quot;low&quot;)</td>
</tr>
</tbody>
</table>

**FIGURE 1.03**
Relationship between the scales of measurement
When you need to figure out what the scale of measurement is for a particular variable, work your way up, asking yourself the questions from Figure 1.04 in order.

If You Answer...

<table>
<thead>
<tr>
<th></th>
<th>Yes</th>
<th>No</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Are the labels meaningful?</td>
<td>Go to Question 2.</td>
</tr>
<tr>
<td>2</td>
<td>Do the labels have an order?</td>
<td>Go to Question 3.</td>
</tr>
<tr>
<td>3</td>
<td>Are the distances between values meaningful?</td>
<td>Go to Question 4.</td>
</tr>
<tr>
<td>4</td>
<td>Is there a meaningful zero?</td>
<td>It’s ratio.</td>
</tr>
</tbody>
</table>

**Nominal** data are data with meaningful labels – that is, the symbols used as data represent something in the real world. Nominal data is qualitative. If you can derive a value and put it in a dataset, it’s at least nominal. Common examples of nominal variables are sex, gender and race. Results from focus groups, rankings, hiring tests and sales are all meaningful labels, so all of our demonstration variables meet this requirement and are therefore at least nominal measurements. A special type of nominal data is **dichotomous** data – these are data with only two possible values (for example, ‘male’ and ‘female’).

**Ordinal** data are nominal data with a meaningful order; that is, they have all the properties of nominal data (meaningful labels) plus ordering. Ordinal data is qualitative. Some values are clearly ‘higher’, ‘more’ or ‘greater’ than others. A common example of an ordinal variable is rank data. Let’s examine each of our demonstration variables:

1. **Opinions from focus groups**: The responses here (‘I didn’t see it’ and ‘I liked it’, for example) do not have a clear order. This variable is not ordinal (nominal only).
2. **Ranked product preferences**: 1st is always better than 2nd, and 2nd is always better than 3rd. These rankings are at least ordinal.
3. **Employment test ranging from 10 to 30**: 30 is always a higher score than 20, and 20 is always a higher score than 10. This test is at least ordinal.
4. **Sales in euros**: More money is always more money. At least ordinal again.

**Interval** data are ordinal data with meaningful distances between values; that is, they have all the properties of ordinal data (meaningful labels that are ordered) plus meaningful distances. Interval data is quantitative. For example, the distance between ‘1’ and ‘2’ is equal to the distance between ‘3’ and ‘4’. A classic example of an interval scale is temperature in degrees Celsius. The difference between 50 and 60 degrees is the same amount ‘hotter’ as the difference between 90 and 100 degrees. Back to our three remaining examples (we already identified focus group opinions as nominal):

1. **Ranked product preferences**: A person who rates Product A as ‘1st’ and Product B as ‘2nd’ may still like both products. The relative standings don’t tell us anything across persons. Ranker A might love both products and Ranker B might hate both products, but each respond with the same ‘1st’ and ‘2nd’. The differences between ranks are therefore not meaningful. Ranked product preferences are not interval (ordinal only).
2 Employment test ranging from 10 to 30: A person with a 30 is always 10 points better than a person with a 20. A person with a 20 is always 10 points better than a person with a 10. This test is at least interval.

3 Sales in euros: 30000€ is always 10000€ more than 20000€. 20000€ is always 10000€ more than 10000€. Sales in this scale are also at least interval.

**Ratio** data are interval data with a meaningful zero point; that is, they have all the properties of interval data (meaningful ordered labels with consistent distances between values) plus a meaningful zero. Ratio data is quantitative. An easy way to figure out if a scale has a meaningful zero is to figure out if multiplying 2 by a value really results in ‘twice’ as many of that value. For example, a common example of a ratio scale is temperature in degrees Kelvin. Zero degrees Kelvin is called absolute zero and can be thought of as the absence of temperature (molecular movement). Ten degrees Kelvin is double the temperature (molecular movement) of five degrees Kelvin. Thus, the zero on this scale is meaningful and degrees Kelvin is a ratio scale. Let’s consider our two remaining examples:

1 Employment test ranging from 10 to 30: A person with a 20 is not necessarily ‘twice’ as employable as a person with a 10. On top of that, the scale only goes down to 10. This employment test is not ratio (interval only).

2 Sales in euros: 0€ really is ‘no sales’. We can also think about it by saying that 20000€ is double 10000€. This scale passes both tests; it is ratio measurement.

Scale of measurement has a lot of implications, as it determines what kind of mathematics (and, ultimately, which statistics) you can use on the values from that scale. Interval scales allow you to use addition and subtraction, while ratio scales allow you to use multiplication and division. For example, it doesn’t make sense to divide temperature in degrees Celsius; 100 degrees is not twice as hot as 50 degrees. So any statistical procedure that would require you to multiply or divide those values could not be used on that scale. These requirements are called assumptions, and they are different for every test. We’ll cover assumptions for each test in detail as we get to them.

There is one exception to the procedure described here, and that has to do with survey data. Surveys often contain a particular type of question called a **Likert-type item**, which is often combined with other Likert-type items into a **Likert-type scale**. Figure 1.05 is an example of a two-item Likert-type scale for product satisfaction.

![Sample Likert-type survey items](image)

With which scale of measurement would you describe the items in Figure 1.05? Let’s go through our list:

1 Are the labels meaningful? Yes, agreement is a meaningful concept.

2 Do the labels have an order? Yes, strongly agree is certainly ‘more’ than strongly disagree, and this order is consistent.

3 Are the distances between values meaningful? Sort of. A five is certainly one point greater than a four, but what about the labels themselves? Is the distance between strongly agree and agree really the same as the distance between agree and neither?
Whether to consider Likert-type data ordinal or interval is a matter of some disagreement among statisticians. The advantage to considering it interval is that this enables you to run more interesting and powerful statistical procedures on the data. The disadvantage is that using these procedures may not result in accurate conclusions if the data really is ordinal. Some fairly complicated arguments have been made in the scientific research literature on both sides.

For the purposes of this text, we will be considering survey data to be interval. But if you are using this text for a course, you should ask your instructor for his or her opinion, just to be safe.

1.1.3 Discrete vs Continuous Data

In addition to scale of measurement, there is one other important distinction when talking about what data looks like.

Continuous data can be subdivided infinitely without losing its meaning. For example, you can add an infinite number of decimal points to a temperature, and it is still a meaningful value. 25.123 degrees is a specific temperature; 25.123623 is, too. We can subdivide smaller and smaller portions, but these values continue to have meaning. Money is typically considered continuous; even fractions of pence are meaningful (just ask a bank manager!).

In contrast, discrete data have only specific meaningful values. For example, the number of applicants for a particular position is discrete, because you can’t have a fraction of a person.

In general, qualitative (nominal and ordinal) data are always discrete, while quantitative (interval and ratio) data may be discrete or continuous.

1.1.4 Determining the Characteristics of Variables

At this point in the text, you should be able to consider any variable and label it with the terms we’ve covered so far. Let’s consider our case study from the beginning of the chapter (Figure 1.06).

<table>
<thead>
<tr>
<th>Case</th>
<th>Store</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>A</td>
<td>2</td>
<td>5</td>
<td>yes</td>
</tr>
<tr>
<td>2</td>
<td>A</td>
<td>2</td>
<td>3</td>
<td>no</td>
</tr>
<tr>
<td>3</td>
<td>B</td>
<td>5</td>
<td>3</td>
<td>yes</td>
</tr>
<tr>
<td>4</td>
<td>B</td>
<td>1</td>
<td>1</td>
<td>yes</td>
</tr>
<tr>
<td>5</td>
<td>C</td>
<td>2</td>
<td>1</td>
<td>yes</td>
</tr>
<tr>
<td>6</td>
<td>D</td>
<td>1</td>
<td>2</td>
<td>no</td>
</tr>
<tr>
<td>7</td>
<td>D</td>
<td>1</td>
<td>3</td>
<td>no</td>
</tr>
</tbody>
</table>

You can see the first problem our owner, Ben, is facing. Without more information, there’s no way to even know the scale of measurement of these values! Fortunately, that can be fixed with another e-mail to the consultant asking some pointed questions like ‘What do these variables represent?’ and ‘What do these values mean?’. The consultant adds a little more information in his reply to Ben:
After customers purchased something at each location, we asked them several questions and recorded it in this spreadsheet. I coded the five locations of Scoops as A through E in the Store variable. Question 1 (Q1) was a five-point Likert-type question to customers, ‘Do you like this store?’, with values ‘Dislike much’, ‘Dislike’, ‘Neither’, ‘Like’ and ‘Like much’. Q2 was a question to customers, ‘How many times have you been to this Scoops in the last six months?’ Q3 was a question to customers, ‘Did you receive excellent customer service?’

We can approach each variable using the same procedures as before. Try to figure out the answers to these questions for yourself before looking at Figure 1.07: ‘Is this variable quantitative or qualitative?’, ‘Is this variable discrete or continuous?’ and ‘What is this variable’s scale of measurement?’.

<table>
<thead>
<tr>
<th>Store</th>
<th>Q1</th>
<th>Q2</th>
<th>Q3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quantitative or Qualitative?</td>
<td>Qualitative</td>
<td>Quantitative</td>
<td>Quantitative</td>
</tr>
<tr>
<td>Discrete or Continuous?</td>
<td>Discrete</td>
<td>Discrete</td>
<td>Discrete</td>
</tr>
<tr>
<td>Scale of Measurement</td>
<td>Nominal</td>
<td>Interval</td>
<td>Ratio</td>
</tr>
<tr>
<td>1 Are the labels meaningful?</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>2 Do the labels have an order?</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>3 Are the distances between values meaningful?</td>
<td>–</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>4 Is there a meaningful zero?</td>
<td>–</td>
<td>No</td>
<td>Yes</td>
</tr>
</tbody>
</table>

### 1.2 Numbers in the Real World

In the second half of this chapter, we’ll consider how to describe the relationship between these numbers and the real world. Remember that a dataset is not just a collection of numbers. Those numbers all have a context – they came from somewhere specific, and that context gives those numbers meaning.

### 1.2.1 Populations vs Samples

When we want to answer a question using data, we rarely have all of the information we want. In the case of Ben’s business, Scoops, there is no way for Ben to ask questions of every past, current and future customer in order to assess customer satisfaction. Ben wants to draw conclusions about ‘customers’ in general, which makes ‘customers’ the population he is interested in.

Populations are the theoretical group that you want to draw conclusions about. If you were interested in people’s opinions, your population would be made up of people. If you were interested in organizational success, your population would be made up of organizations. Populations are generally not measurable directly because they are too large, they are too unwieldy or it would otherwise be too impractical to do so. Yet we want to make a conclusion about these groups! So what do we do?
The answer: we get a sample. Samples are groups of subjects drawn from a population at random – see Figure 1.08. Because samples are much smaller than populations, we can more realistically collect measurements from those samples. In our case study, Ben is interested in all ‘customers’ (the population), but because it is unrealistic to assess every customer, the consultants asked only those who had just purchased something at Scoops. The customers that were asked questions are the sample.

So how do we know that conclusions drawn from our sample reflect the conclusions we would have drawn if we had the population? If Ben concludes ‘customer satisfaction is lowest at Store D’, how do we know that’s really because customer satisfaction is lowest at Store D (a question about the population) or because the people that by chance were shopping that day at Store D were less satisfied (a problem with the sample)?

Unfortunately, we can never know for sure! This is a question of how representative the sample is of the population. If the sample is highly representative, conclusions drawn from the sample are likely to reflect conclusions that would have been drawn from the population. If the sample is not representative, conclusions drawn from the sample are unlikely to reflect the population.

Representativeness can never be assessed with numbers. It is a rational argument. For example, Ben might realize that the sample taken from Store D was taken during a rush period, while the samples taken from the other stores were taken during slow periods. Customer service will generally be poorer during the rush period (more customers, less individual attention), but this does not mean that Store D is poorer in customer service than any other store. Instead, Ben is making an argument that a sample of customers purchasing during the rush period is not representative of a population of all customers, and therefore conclusions from that sample cannot be used to make conclusions about the population.

When trying to address a research question, you must decide on the population you are interested in, and then identify a sample you can reasonably approach that should represent that population. There are ways to increase the representativeness of a sample – larger samples, for example – but we’ll get to this topic in more detail in Chapter 5: Sampling Distributions.

1.2.2 Constructs vs Operational Definitions

Just as we need to worry about how our samples represent the populations we wish we could study, we must also consider how the numbers we collect represent the concepts we wish we could study.
In Ben’s case, he is really interested in a hypothetical idea called ‘customer satisfaction’. There is no way to measure customer satisfaction directly. We can’t, for example, walk up to a customer with a ruler and assess their satisfaction. That means customer satisfaction is a **construct**, which can be defined as a characteristic or property of interest in a population that cannot be measured directly.

When we have specific beliefs about what might be true in the relationship between constructs, we have a **theory**. In our case study, Ben has a theory that customer satisfaction is different between different stores. Because customer satisfaction is a construct, there’s no way to measure it – but that doesn’t make the theory any less interesting.

Now that we have a theory linking several constructs, we need a way to test this theory in the ‘real world’. The first step is to identify an **operational definition** for each of our constructs. An operational definition is the way we represent a construct in a dataset, and we sometimes refer to this definition as the **operationalization** of a construct. The link between a construct and operational definition, just like the link between a population and a sample, cannot be demonstrated with numbers. It too is a rational argument.

In our case study, ‘customer satisfaction’ was operationalized with Questions 1 through 3 (Q1–Q3), while the identity of the store was operationalized as a letter (A–E). In each of these cases, Ben left it up to the consultant to determine what the best operationalization might be. If this operational definition doesn’t make sense, it might explain why the results were not as Ben expected. Is a Likert-type question the best way to assess customer satisfaction? Is a simple yes/no question about customer service better? There is no clear ‘right answer’ here. The only way to show that this is a good operationalization is for Ben or the consultant to make a solid argument as to what makes the most sense.

After deciding on operationalizations of each of our constructs, we can now test our theory by creating a **hypothesis**, which is a testable relationship between operational definitions that reflects a theory. Because we can never actually test a theory, because constructs can never be measured, we can only create a set of operational definitions and test the relationships between them. If all of our rational arguments make sense (if our operationalizations reflect our constructs, and if our sample represents our population), then we have built a case to say: ‘if we find evidence supporting our hypothesis, our theory is probably true.’ We will get into the specifics of this argument in later chapters.

In Figure 1.09, you can distinguish between hypotheticals and the ‘real world’ by looking at the dotted line. Anything above or that crosses that line is theoretical and can only be ‘proven’ by making a rational argument that it is true. Anything below that line can be demonstrated with numbers (measured).
Experiments, Quasi-Experiments, and Correlational Studies

Now that we have a hypothesis, we need to test it in a way that tells us something interesting. Just because we have numbers doesn’t mean they’re telling us the truth – this depends upon how the data is collected and analyzed.

There are three major approaches to testing a hypothesis in a business context: an experiment, a quasi-experiment or a correlational study – see Figure 1.10. Each brings different advantages and disadvantages.

The most rigorous approach is an experiment. This is the only approach that allows you to conclude something causes something else. For example, if our hypothesis was ‘increased customer satisfaction causes sales’, the only way to demonstrate this would be with an experiment. Unfortunately, an experiment is the most difficult approach to implement.

To run an experiment, you split a sample randomly into two or more groups called conditions, a process called random assignment. You can then treat each condition differently and observe any resulting differences between the groups. Because you assigned the people to each group at random, the only difference between the two groups should be the way you treated them differently.

For example, imagine that you were considering a new training programme for your employees. You need to pay for each trainee, so you’d like to know if the training works before you purchase it for everyone. You decide to run an experiment. You randomly pick half of your employees to receive the training (the treatment condition), while the other half will receive nothing (the control condition). A few months after the training, you check to see if job performance is higher for the group that received the training. If so, you can conclude that the training caused the higher level of performance (and purchase it for everyone!).

As you can see, the restrictions and planning required for an experiment are rather extensive. There are many situations where experimentation is not realistic or is downright impossible. For example, consider our original question: does increased customer satisfaction cause increased sales? We cannot randomly assign customer satisfaction, so an experiment is not possible here.

When an experiment is not possible, a researcher often uses a correlational study. A correlational study is any study where multiple variables are measured at the same time without special treatment by the researcher. We can never make conclusions about causality from correlational studies. For example, we could see if there are differences in customer satisfaction by store. We can’t randomly assign stores, so we can never conclude that the management, employees, or anything else about those stores causes those differences in satisfaction. While the store might cause these differences, there is no way to support this theory with a correlational study. Despite this, determining if there is a relationship between two variables may be a valuable piece of a puzzle to be solved.
One type of correlational study is worth special discussion, and this is the quasi-experiment. Quasi-experiments look like experiments on the surface, but lack random assignment of subjects. For example, consider our training programme above. Instead of randomly picking half of your employees to receive the training, you ask for volunteers. Now, instead of drawing from a single population (employees) and randomly assigning them to conditions, you are drawing from two populations (volunteers and non-volunteers) and letting them choose their own conditions. This is a problem, because if the trainees ended up performing better, you would have no way to know if this was because the training works for all employees or only for enthusiastic volunteers.

It’s also important to note that random assignment must take place at the level of the subject, or it is still a quasi-experiment. Consider our training example. Instead of randomly assigning all employees to either training or no training, what happens if you randomly assign day shift to training and night shift as the control? Despite having a treatment and control condition, this is still a quasi-experiment, because these are two different populations. There is no way to know if any observed differences were caused by the treatment (getting training) or instead because of pre-existing differences between the people working in those shifts.

If experimentation is possible, you always want to conduct an experiment, because it will give you the highest quality answer to your questions. Quasi-experiments and correlational studies are always a backup choice. But sometimes, they’re the only choice.

1.2.4 Determining the Characteristics of Studies

Now that we have all these terms to describe study design, can we apply these terms to help Ben figure out if he should trust the consultant’s conclusion: ‘Decreased customer satisfaction does not lead to decreased sales at Scoops’? Let’s return to the first line of that follow-up e-mail from the consultant:

‘After customers purchased something at each location, we asked them several questions and recorded it in this spreadsheet.’

That’s relevant to the sample and population. The sample assessed appears to be made up of customers that have purchased something and elect to complete a survey afterwards. Does this reflect a population of customers in general? Maybe, maybe not. But that’s something Ben needs to decide for himself.

What constructs and operational definitions are we talking about? Did at least these operationalizations make sense? It’s not clear which questions the consultant used to make these conclusions. Our constructs of interest are ‘customer satisfaction’ and ‘sales’. So which questions were used to assess these?

Q2 was ‘How many times have you been to this Scoops in the last six months?’ and is the closest we have to ‘sales’. Q3 was ‘Did you receive excellent customer service?’ and is the closest we have to ‘customer satisfaction’. Are these reasonable operational definitions for these constructs? Again: maybe, or maybe not. A customer may not be able to remember how many times he’s been to a particular location over six months. Number of visits rather than money spent may not be the best way to assess sales. A single question about customer service might not include all aspects of customer satisfaction: satisfaction with employees’ attitudes, satisfaction with employee speed, satisfaction with employee attention, and so on. None of these criticisms necessarily condemn this study, but they are things that Ben needs to consider. Does he believe these operational definitions really represent the constructs they are designed to represent? If not, then this study is not credible.

When the consultant concluded that ‘Decreased customer satisfaction does not lead to decreased sales at Scoops’, he made a conclusion about causality. Lead to implies that satisfaction caused sales. Is that conclusion justified? The consultant did not create
conditions and assign people to them; he passively collected information from customers as they left. This is a correlational study; any conclusions about causality are not justified. This conclusion cannot be made from this study.

With weaknesses in the population being sampled, the study design and the operational definitions of the constructs, Ben should conclude that this study (and this consultancy) is not credible. Even though they collected data, they are not drawing appropriate conclusions from that data. Collecting numbers is not enough to tell a credible story; the source of those numbers must also be sound.

1.3 Applying the Language of Statistics

To apply what you’ve learned from this chapter, consider the following case study, questions posed about that case study, and discussion of those questions.

1.3.1 Application Case Study

Maya is a manager for We Get You There, a small travel agency that arranges family vacations. Each of the agents at her agency is assigned clients by alphabetical rotation—that is, when a new client contacts the agency, that client is assigned to the next agent down the list, repeating from the beginning. As a result, clients are shared equally among all the agents, ensuring that no one agent is favoured above any other. This creates a very friendly work environment, but Maya is concerned that it is hurting agency profits. After all, skill as a travel agent varies a great deal, and her less skilled agents work with as many clients as her most skilled agents.

1. If Maya is interested in examining whether or not agent skill is affecting company profits, what variables could she examine?
2. Pick a few variables of interest for Maya. What are their scales of measurement? Are they discrete or continuous?
3. How could Maya examine these variables? What research design is most appropriate?

1.3.2 Application Discussion

The path from research question to research study is one of the most difficult we face as managers and owners. In Maya’s case, there are many possible ways to answer her question, and the ones you come up with are probably not the one we will discuss here. However, this will serve as a reasonable prototype.

Maya is interested in the relationship between agent skill and company profits. That means agent skill and profits are her two constructs of interest. When we seek to create variables, we are really creating new operationalizations of those constructs. There are an infinite number of ways to do this. However, we might operationalize agent skill with a test. For example, Maya might ask her agents to run through a sales simulation to gauge their effectiveness. Alternatively, Maya might conduct surveys of clients, asking them about their experiences with their agent. To operationalize the effect on company profit, Maya could examine the total amount of sales over some period of interest.
Scale of measurement will change dramatically depending on what Maya chooses. A simulation test could produce many types: a ‘pass/fail’ test would be nominal (and discrete), but a test that produced a score would be interval or ratio (and could be discrete or continuous, depending on the specific scoring technique). If she chose a survey, this could be anything, depending on the types of questions asked. Total sales might be computed in British pounds of services sold per month, which would be continuous and ratio. However, it could be computed as a total count of sales, in which case it would be discrete and ratio. It all depends on what Maya chooses.

For research design, we face a common problem in business: there is no way to randomly assign agents to be ‘good’ or ‘bad’. As a result, Maya most likely needs to passively measure her variables and compare them: a correlational design.

EXPLORING THE LANGUAGE OF STATISTICS IN EXCEL AND SPSS

Excel

Download the Excel dataset for the demonstration below as chapter1.xls. As you read this section, try to apply the terms you’ve learned in this chapter to the dataset and follow along with Excel on your own computer. You can also get a video demonstration of the section below under Excel Videos: Chapter 1.

Excel is a very flexible spreadsheet program, but it is not principally designed for computing and analyzing statistics. As a result, it doesn’t have quite the power of SPSS to answer statistical questions. Despite this, it is advantageous to learn Excel for analyzing statistics because it is a much more common program than SPSS; you can find Excel and similar spreadsheet programs like OpenOffice.org Calc on computers throughout the world.

A dataset in Excel is saved in a worksheet, which you can access via the tabs at the bottom. Otherwise, it’s very similar to the diagram earlier in this chapter – compare Figure 1.01 and Figure 1.11. To enter data, just click and type.

FIGURE 1.11
A dataset as shown in Excel

SPSS

Download the SPSS dataset for the demonstration below as chapter1.sav. As you read this section, try to apply the terms you’ve learned in this chapter to the dataset and follow along with SPSS on your own computer. You can also get a video demonstration of the section below under SPSS Videos: Chapter 1.
THE LANGUAGE OF STATISTICS

Because it is specifically designed for computing and analyzing statistics, SPSS is a very powerful program for computing a wide variety of statistics. With increased flexibility, however, comes increased complexity. Working with data in SPSS requires a bit more work up front than it does in Excel.

There are two views of interest in SPSS. The first is the Data View, which displays your dataset. It looks a lot like the spreadsheet that appeared earlier in this chapter – compare Figure 1.01 and Figure 1.12. The biggest difference is that SPSS automatically creates a column of case numbers, so you don’t need to add them yourself. Cases with data in them appear with black text, while empty cases appear with grey text.

Using the view selector at the bottom, you can also gain access to the Variable View, which allows you to set the properties of your variables. The settings you choose here help SPSS to decide how to treat your variables in analyzes.

In the variable view, you can see the same four variables we saw in the data view, but with a lot of extra settings for each one (see Figure 1.13).

- **Name:** This is the word used at the top of the column in your variable view. You can’t start a variable name with a number, spaces or special characters.
- **Type:** This is the general format for the data contained in this variable. The two options you’ll use most often are Numeric (for numbers) or String (for text).
- **Width:** This is the number of characters recorded for each datum. For example, if you have a string of Width 2 and try to enter ‘Yes’, it will be truncated to ‘Ye’.
- **Decimals:** When using numeric data, this determines how many numbers after the decimal place will be displayed. It does not affect how many numbers are stored. For example, if you stored 12.3456 in a variable with 2 for Decimals, you would see ‘12.35’ in the Data View, even though 12.3456 would be used in statistics calculations.

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- **Label**: These are the words you’ll see in place of the variable name when running statistical analyzes. For example, if we computed an average for ‘Q1’, the results would label it, ‘Do you like this store?’. This is only used to make output more readable, and has no effect on the results.

- **Values**: These are the words you’ll see in place of the numbers used for each datum in analyzes. In this example, clicking on the [...] button brings up the panel shown in Figure 1.14. With this set of values, 1 through 5 will be replaced with these words to make the output more readable. This also has no effect on results.

![Figure 1.14](image)

- **Missing**: This allows you to set missing values. This is an important component of statistical analyzes in the real world, but involves a lot of complicated decisions you’ll talk about more in a research methods class. In this statistics text, we’ll just be leaving this unset.

- **Columns**: This sets how wide the variable appears in the Data View. You can change this manually by click-dragging the width of the columns in the Data View.

- **Align**: This sets the text alignment of each variable in the Data View. This has no effect on results.

- **Measure**: This is one of the most important parts of the Variable View. Setting this tells SPSS which scale of measurement your variable is, which in turn tells it which analyzes are appropriate for that variable. There are three options. Select **Nominal** for nominal variables and **Ordinal** for ordinal variables. Select **Scale** for both interval and ratio variables.

**TEST YOURSELF**

Answers to the odd-numbered questions can be found in Appendix C.

1. Sally, the owner of Two Pi Are Pizza, decides to conduct a research study to determine if adding double cheese free of charge to pizza orders improves customer satisfaction. Sally adds a customer satisfaction survey with Likert-type scales to every pizza box. She randomly assigns her stores on the west side of the city to change their procedures to use extra cheese and plans to compare these with stores on the east side of the city, where nothing will change.

   a. Is this an experiment, quasi-experiment or correlational study, and why?
   b. Can Sally provide evidence that extra cheese causes increased customer satisfaction using this design? If not, how could she change this design so that she can?
c What is the treatment and what is the control condition?
d What is a possible hypothesis for Sally’s study?
e Is Sally drawing her participants from a sample or a population?
f What constructs are being assessed, and how are they being operationalized?
g Are the addition of a free extra cheese variable and the Likert-type scales collected here quantitative or qualitative?
h Are the addition of a free extra cheese variable and the Likert-type scales collected here discrete or continuous?
i What are the scales of measurement of the addition of a free extra cheese variable and Likert-type scales as assessed here?

2 Jimmy, the manager of one of Sally’s pizza shops, decides to conduct a research study to determine if his happiest employees are also his highest-performing employees. He watches all of his employees without their knowledge and quietly records the number of times he witnesses them smile in each day. He then compares these values with their most recent overall performance evaluation scores, which is a single value between 1 and 5 (1 = terrible employee; 5 = perfect employee).

a Is this an experiment, quasi-experiment or correlational study, and why?
b Can Jimmy provide evidence that happiness causes increased performance evaluations using this design? If not, how could he change this design so that he can?
c What is the treatment and what is the control condition?
d What is a possible hypothesis for Jimmy’s study?
e Is Jimmy drawing his participants from a sample or a population?
f What constructs are being assessed, and how are they being operationalized?
g Are the number of smiles and performance evaluation scores collected here quantitative or qualitative?
h Are the number of smiles and performance evaluation scores collected here discrete or continuous?
i What are the scales of measurement of the number of smiles and the performance evaluation score as assessed here?

3 Ben, the owner of Scoops, decides to hold a frozen yogurt eating contest to promote the opening of a new store. He decides to collect some data about the contestants in the contest to include on his website. Identify the scale of measurement for each of the variables he measured:

a Age
b Favourite flavour of frozen yogurt
c Order of finish in the contest (i.e., 1st place, 2nd place, 3rd place)
d How much the contestant reported liking frozen yogurt on a 1–5 scale
e The number of eating contests the contestant had previously participated in
f Where the contestant lives

4 Sally, the owner of Two Pi Are Pizza, decides to collect information about her delivery service customers in order to provide better delivery service. Identify the scale of measurement for each of the variables she measured:

a Size of pizza ordered
b Number of pizzas ordered
c Day of the week the order was placed
d Delivery distance
e Time of day when the delivery occurred
f Amount of delivery tip

5 Produce an operationalization of ‘successful online social media strategy’. Describe this operationalization in the terms we’ve used here to describe variables.

6 Produce an operationalization of ‘positive attitude toward a product’. Describe this operationalization in the terms we’ve used here to describe variables.

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CHAPTER 1

DATA SKILL CHALLENGES

1 Five people completed a five-item Likert-type scale. Here are their scores:
   George: 1, 2, 3, 4, 5
   Bill: 2, 2, 3, 3, 3
   Amy: 5, 5, 4, 5, 5
   Jonathan: 4, 3, 2, 1, 1
   Stephanie: 3, 3, 2, 2, 5

   Place these scores into a dataset, organizing it into rows and columns as appropriate. Remember to include the person’s name in your dataset as appropriate.

2 Here are data for the top three finishers in Ben’s frozen yogurt eating contest (see Question 3 above):
   Anton: 16, Vanilla, 1st, 4, 5, Newton
   Jemia: 37, Chocolate, 2nd, 5, 0, Blackwell
   Harry: 22, Strawberry, 3rd, 3, 21, Newton

   Place these scores into a dataset, organizing it into rows and columns as appropriate. Remember to include the person’s name in your dataset as appropriate.

3 Here are data for Sally’s first four deliveries:
   Customer 1: Large, 1, Thursday, 2 km, evening, £2
   Customer 2: Medium, 2, Thursday, 4 km, evening, £3
   Customer 3: Small, 1, Friday, 3 km, afternoon, £1
   Customer 4: Extra Large, 2, Friday, 1 km, evening, £4

   Place these scores into a dataset, organizing it into rows and columns as appropriate. Remember to include the customer number in your dataset as appropriate.

4 Here are sales data for the branch offices of a large sales organization:
   Branch 1: West region, 20 units sold, 34000€
   Branch 2: West region, 40 units sold, 50000€
   Branch 3: East region, 16 units sold, 35000€
   Branch 4: East region, 93 units sold, 85000€

   Place these scores into a dataset, organizing it into rows and columns as appropriate. Remember to include the branch number in your dataset as appropriate.

NEW TERMS

- case
- conditions
- construct
- continuous
- control condition
- correlational study
- data
- Data View
- dataset
- datum
- dichotomous
- discrete
- experiment
- hypothesis
- interval
- Likert-type item
- Likert-type scale
- nominal
- operational definition
- operationalization
- ordinal
- population
- qualitative
- quantitative
- quasi-experiment
- random assignment
- ratio
- representative
- sample
- scale of measurement
- subject
- theory
- treatment condition
- variable
- Variable View