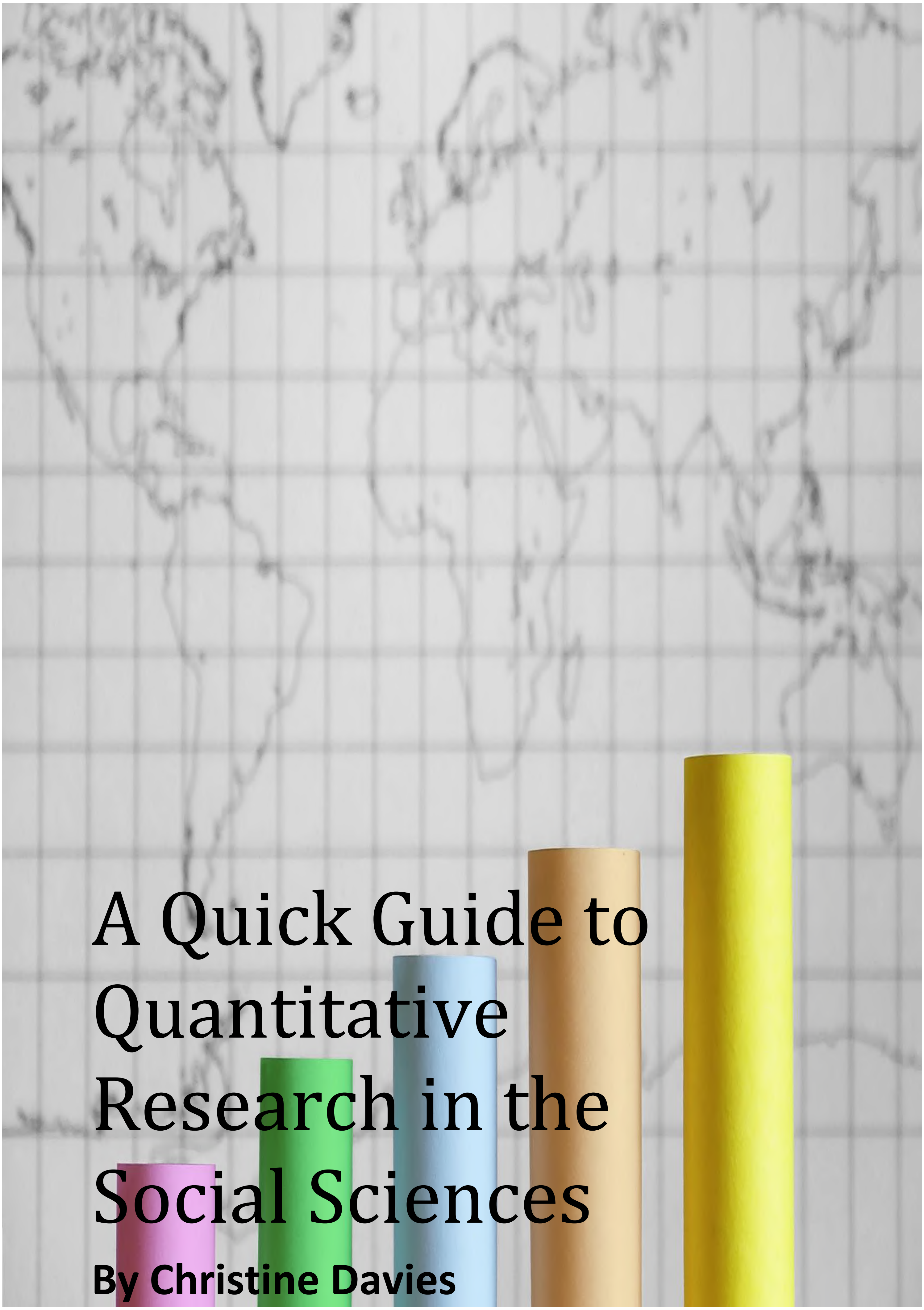

A Quick Guide to Quantitative Research in the Social Sciences

By Christine Davies

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Contents

Section 1: What will this resource do for you?

This resource is intended as an easy-to-use guide for anyone who needs some quick and simple advice on quantitative aspects of research in social sciences, covering subjects such as education, sociology, business, nursing. If you are a qualitative researcher who needs to venture into the world of numbers, or a student instructed to undertake a quantitative research project despite a hatred for maths, then this booklet should be a real help. If, however, you have a degree in statistics and/or a large laboratory, you're unlikely to benefit from it.

If you are happy to start simply, and build up your knowledge gradually, then this guide will suit you, and should act as a basic but reliable road map. Very little existing knowledge is assumed, and examples from a range of social sciences are given at the end of each key section to put concepts into context.

Note that this guide contains few detailed explanations, so other texts are signposted at intervals. You are encouraged to read more deeply about items that may be useful to you so that you have a better understanding of key concepts. Likewise, no attempt is made to go through the mechanics of statistical tests because most researchers have access to software which does all this (you do need to know how to use the software, however!).

Hopefully, you will find this guide easy to use, and quick to give answers. It is intended as a resource that you can come back to every time you start a new piece of quantitative research. The first time you use it, it would be sensible to read it all the way through so that you get an overview of the whole research process.

Section 2: Why are you thinking about numbers? A discussion of the research question and paradigms.

There are many instances in which essentially qualitative researchers find themselves heading for quantitative terrain. For example, a language teacher may need to monitor the marks of large numbers of pupils, or a psychology student undertaking a study on retail behaviour may first need to obtain numbers of people displaying contrasting behaviours. There may alternatively be a need to measure impact or effect. **Generalisability** may also be required, ie. finding general principles that could apply across a wide range of individuals and contexts.

Whatever your context or requirements, you should only consider quantitative methodology because your **research question** requires it. This is important irrespective of your subject, or the type of researcher you are: you should be clear why you need to move in a quantitative direction before you start out.

A researcher's **paradigm** is also very important. This is the overall world-view that guides the direction and type of research. Those whose research is predominantly quantitative are likely to have an objectivist ontology and positivist epistemology, and usually seek empirical evidence based on numbers. Many users of this guide will hail from more subjectivist territory, but because their research question involves some numerical aspects, they find that their overall paradigm tends towards the pragmatic.

Table 1: A brief summary of some paradigms which may lead to quantitative research

Paradigm	Description	Example
Positivist	A belief that knowledge is best gained by examining empirical, objective data	Botany student studying the effects of micronutrients on plant growth
Realist	View that reality is imperfectly described purely by objective measurements	Psychologist who asks about perceptions as well as recording electrical activity
Pragmatic	The research question may need more than one approach in order to obtain a full answer. There is	Sociologist who needs to explore the extent of a practice before finding reasons for it

	also an awareness of what is practically possible	
Critical	The objective of the research involves change and/or improvement	Researchers looking at the lives of women in an African region, aiming to find ways they could be improved

Need more information about Paradigms? Go to:

Blaikie, N. and Priest, J. (2016) Social Research: Paradigms in Action.

Literature Review

Before carrying out any research, quantitative or qualitative, it's important to find out about the existing research in your subject area. Your work should build on this rather than duplicate information. The sources of information that you locate will form the basis of your Literature Review. Use your university library catalogue, subject databases, and even Google Scholar, to seek out recent articles and books, preferably peer-reviewed (ie. judged acceptable by other researchers). Read them with a critical eye, looking for the ones that give key information, including useful approaches to Research Design. Keep track of everything you read (which could involve using referencing software such as 'Refworks'), and note down all important points.

Example: *Mari, a theatre manager*:

"I know we're not doing things as well as we could be, and I want to get evidence that backs up my gut instincts, and helps me see what new strategies I should put in place".

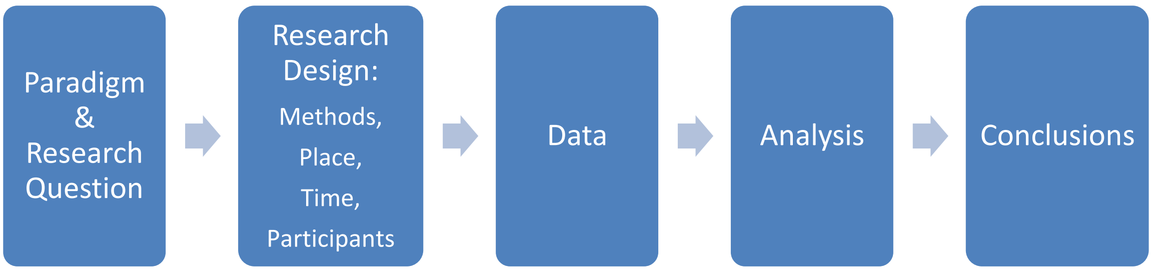
Mari's **Paradigm:** Probably critical, because she wants change

Mari's **Research Question**: something like: "How has audience satisfaction at a theatre changed over the past ten years, and how could it be improved?"

Section 3: An overview of the Research Process and Research Designs

Once you are clear about your research question, you need to start planning how you will carry out your research. This is where Research Design comes in: this summarises all aspects of the proposed research including practical aspects such as when and where the research will take place. Your Research Design should clearly indicate where and how quantitative elements are incorporated, and you should also decide right from the start what sort of data you will generate, and how you will analyse it (the details of types data and data analysis are covered later). When it comes to writing up your work, you would normally explain your Research Design and associated Research Methods within the 'Methods' section (or 'Methodology and Methods').

Figure 1: The Research Process



Research designs involving Quantitative methodology are usually either **exploratory** or **confirmatory**. Exploratory designs are **inductive** – they involve discovering and describing. Confirmatory designs, by contrast, generally begin with a research question which is tied to a hypothesis (more on this later), and they are therefore said to be **deductive**.

There are several research designs used in the social sciences which contain quantitative elements:

Mixed methods: this is a common research design in the social sciences, and comprises both quantitative and qualitative elements, often with an exploratory approach. A typical example of a mixed methods design could involve a survey of employees in an organisation to gauge job satisfaction, followed by a small number of interviews aiming to explain survey findings.

Case Study: A case study collects different sorts of data about a specific case, which could be a person, place, process, etc. Case studies are common in social sciences, and are almost always exploratory, and frequently purely qualitative, but there may be some quantitative aspects. For example, a case study of a community space might include counts of people visiting the space, as well as more qualitative elements such as photographs in different seasons, and interviews with users.

Quasi-experiment: Experimental research designs are almost always confirmatory, and generally involve at least two groups or situations which are compared in some way. For example, a school may decide to try out a new reading method in one class, but continue with the previous method in another class. This would not be a true experimental design because the selection of participants is not random, and not all of the factors involved can be controlled. Many experimental research designs in the social sciences are like this, and would hence be termed 'naturalistic experiments' or 'quasi-experiments'. In this type of design, the researcher has to be careful about 'confounding' **variables** (a variable is a factor that has variable numerical levels) which may influence results (in this example light and heat levels, or tiredness of the children, might have a bearing on reading performance). A well-known example of research where confounding variables had a major effect is known as the 'Hawthorne Effect' (see Adair, 1984).

Action Research: Action Research generally involves a cycle of events starting off with planning, followed by an intervention which is designed to improve. Data are then collected to provide evidence of what actually happened as a result of the intervention. Reflection on these data forms the basis of the next action research cycle. Action Research is often considered a qualitative research design, but quantitative elements may be incorporated in order to obtain numerical evidence of the efficacy of one or more implementation steps.

Need more information about Research Designs? Go to:

- Denscombe, M. (2014) *Good Research Guide For Small-Scale Social Research Projects*. 5th ed. McGraw-Hill Education.
- Creswell, J.W. (2009) *Research Design: Qualitative, Quantitative, and Mixed Method Approaches*. 3rd ed. London: SAGE.

Example: *Peter, a student nurse*

Research Question: "Does the time of day when medicines are dispensed have an effect on blood pressure reduction in geriatric patients in Hospital A?"

Research Design: Experimental/ Quasi-experimental.

Peter could choose, say, three different times of day for dispensing medication, and randomly assign geriatric patients to each of these times (so there would three different groups of patients, ideally with a fairly large number of patients in each group). For every patient, he would have to measure blood pressure at a specific time interval before and after dispensing medication (pre- and post-test measurement). This wouldn't be a true experiment unless Peter can control all other relevant variables (such as volume of tea drunk, degree of movement, visits to lavatory!).

Research Proposal

Once you feel you have a good grasp of your topic, a sound research question, and clear idea of Research Design, you would normally produce a research proposal. This usually starts with an Introduction, providing the context and rationale for your research, followed by an indicative Literature Review, explaining the key research informing your work. Lastly, the proposed Methods are outlined. At this stage, before any research has commenced, you also need to consider ethical issues such as gaining informed consent from your participants, and any necessary permissions from organisations involved. It is important to adhere to relevant ethical guidelines and codes of practice, and it is often necessary to undertake a process of ethical approval. As part of that process, you should also consider whether you need to store any personal data, bearing in mind legal requirements such as the General Data Protection Regulation, 2018 (GDPR) in the EU. You also need to plan how to store your data securely. A repository may be a good option, especially if you have links with a university or similar.

Need more guidance on planning your research? Go to:

- Thomas, G. (2017) *How to Do Your Research Project: A Guide for Students*. 3rd ed
- University of Leicester (2019) *Effective Planning of the Research* [online]. Available at: https://www.le.ac.uk/oerresources/ssds/writingskills/page_83.htm (accessed 17.02.20)

Section 4: Quantitative Research Methods

The research methods you choose for your **primary research** (ie. obtaining new data) will depend on your research question and research design. You will also need to select participants, of course. In quantitative research, unlike in qualitative, it's important to have fairly large numbers of participants, and this is discussed further in the section on Surveys. Three quantitative research methods are outlined below, though note that you will sometimes see terms such as 'experiment' used as a method as well as a design.

Note that research designs may include **secondary research** that is quantitative in approach, ie. examining numerical data generating by previous research. The process of analysis such data is called **secondary analysis**.

Measurement

Quantitative research often involves direct measurement, such as the height of children, attendance at rugby matches, or daily supermarket sales. Specific disciplines may have their own scales and **indicators**, such as IQ ('Intelligence Quotient'), or may have varied approaches to measurement. For example, a nurse may gauge patient progress based on the paleness of skin, or conversational ability, as well as conventional measures such as body temperature and blood pressure.

Observation

Although observation is often highly qualitative in nature, for example in ethnographic research designs, it can also have quantitative elements. Researchers in factories may need to observe how long it takes to undertake a particular production task, for example, and teachers may wish to monitor the number of 'hands up' when a particular question is posed.

Surveys

One of the most widely used quantitative research methods used in social contexts is the survey. This involves the distribution of a *large* number of questionnaires (note that if only a few questionnaires are used then it's not really appropriate to use the word 'survey').

It is rarely possible to access the whole **population** of interest (though that may not be a problem if the population is, say, all the children in a school), so a survey usually involves obtaining responses from a **sample** of the population. Researchers often aim to select a **random sample** which is large enough to be representative of the population. It's possible to estimate the minimum sample size required assuming certain key variables, and this can be done using online sample size calculators (eg: https://www.qualtrics.com/blog/calculating-sample-size/).

Questionnaires are generally administered via paper copies distributed by post or by hand, or completed online. Online survey tools such as SurveyMonkey (https://www.surveymonkey.com) are useful because they ensure **anonymity** (which may not be the case with email distribution), and they also incorporate tools that allow for a range of analyses (note that some organisations are very particular about which survey tools are acceptable, so it's best to check before use). Questionnaires are often completed by participants themselves ('self-completion'), though they could also be completed via structured interviews, in which an interviewer asks the questions. This may help to get valid responses, and hence improve **response rate**, but it is a time-consuming approach.

A good questionnaire should be visually appealing, and the way questions are worded and/or depicted should be thought about carefully. Questions and answer options need to be clear for all participants to ensure that there are no misunderstandings and hence inaccurate responses. Surveys often have a mix of different types of questions, some of which are 'open' and hence more qualitative in approach. Quantitative survey questions generally involve some type of numerical scale, often a **Likert scale**, with numbers acting as an **indicator** for concepts such as 'satisfaction' or 'confidence'. For example, leadership potential could be gauged from 1 to 4 on a Likert scale. Note that using a scale in this way may not be appropriate to the concept being investigated, and analysis of the data obtained needs to be handled with care (see later section).

Need more information about setting up Surveys? Go to:

- Bryman, A. (2008) *Social Research Methods* (3rd ed.) Oxford: Oxford University Press.
- Fink, A. (2002) The Survey Handbook (2^{nd} ed.) London: Sage.

Example: *Kim, a Deputy Headteacher in a primary school*

Research Question: "What are parents' opinions of recent changes to grading and assessment procedures?"

Research Design: Mixed Methods

Research Methods: *Survey* to all parents (quantitative element) to obtain numerical rating of key aspects of assessment, followed by *interviews* with a random sample of parents to obtain explanations for their ratings

Section 5: the data obtained from quantitative research

When you work out your research design, and especially when you consider data analysis, you need to think about the type(s) of data you will generate. Data comes in three main forms:

Table 2: An outline of the main types of data

Data type	description
Scale (or 'Interval/ratio') data	Numerical data with clear, fixed intervals (eg. 1,2,3).
Ordinal data	Data which can be rank ordered, but with intervals that are not clear/fixed (eg. 'agree' and 'agree strongly')
Categorical (or 'nominal') data	Data which describes categories or names (ie. qualitative data) (eg. red, green, blue).

The best sort of data from the perspective of quantitative research are **scale data**. This is particularly the case if your research question involves possible relationships, and if this is the case you should aim to measure **continuous scale variables**. These are variables that fit well on a scale, and may have intermediate values, for example: 2 years, 2.5 years, 2.75 years.

Note that it would be usual to put your 'raw', unanalysed, data in an Appendix, with a summary of your data in a Table in the 'Results' section of your report/article/thesis.

Section 6: Analysis of data

The data produced from quantitative research can be analysed using both **descriptive** and **inferential** statistics. Note that the word 'statistics' implies dealing with sample data (the word '**parameter**' would be appropriate when discussing populations).

Descriptive statistics

These involve summarising and depicting data.

One type of descriptive statistics are **average** values, or measures of '**central tendency**' such as:

- **Mean**: sum of all values divided by the number (or frequency) of the values. For example, the mean age of patients on a ward)
- **Mode**: most common value. For example, the most common test results amongst a cohort of students
- **Median**: value mid-way through the whole range, with 50% of values below, and 50% above. For example, the height that is mid-way through the range of heights in a class of children

Less often, measures of '**dispersion**' are reported. These indicate how spread out the data are:

- **Range**: largest value minus the smallest. For example, the difference between the longest time and the shortest time taken to complete a key manufacturing step in a shoe factory.
- **Standard deviation**: the average amount by which sample values vary from the mean. For example, a sample of bags of sugar might not all be exactly 2kg, as required. But on average, the amount by which they vary might be quite small, maybe just 3g.

These measures are easily calculated in applications such as MS Excel, or by calculators. They may be noted in tables and presented in the 'Results' section.

Table 3 shows a typical summary of results table (tables of this type may also be known as 'pivot tables' or 'crosstabs'). Descriptive statistics such as means could also be added in (eg. mean number of managers per site).

Table 3: typical Summary of Results Table

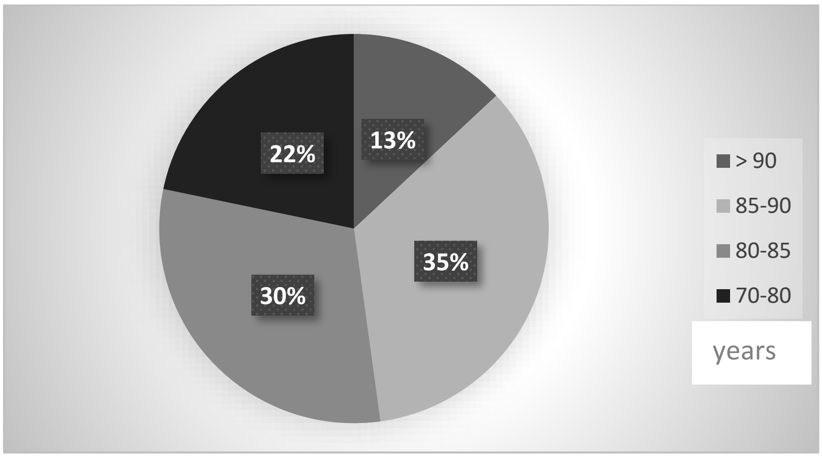
Table to Show numbers of management-related staff at three different sites of the same firm

	Management category			**Totals per site**
Site	**managers**	**Trainee managers**	**Not management**	
A	4	13	26	43
B	1	9	15	25
C	5	17	28	50
Total per category	10	39	69	118

It may also be useful to show data in diagrammatic form within your Results, and charts and plots of the sort shown below can be produced very easily with software such as MS Excel.

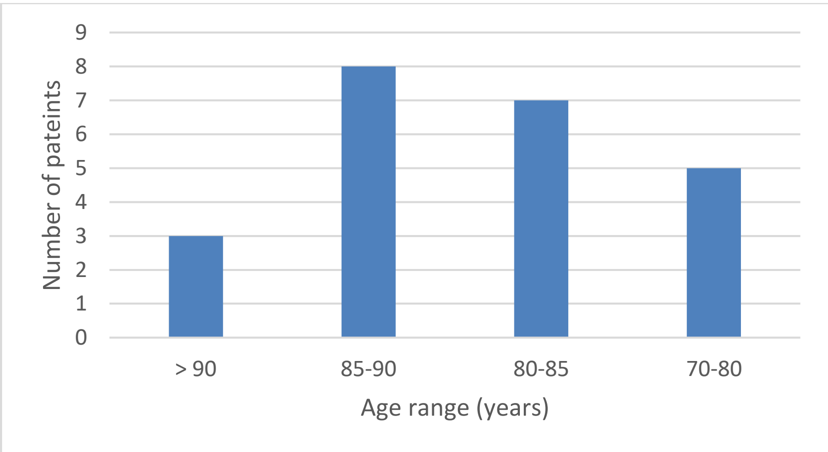
Figures 2 and 3 show the same data depicted in two different forms:

Figure 2: Pie chart to show proportion of patients in different age ranges in a geriatric ward



Note that you should always include a title to all charts, and a key (if there are different colours etc)

Figure 3: Bar chart to show actual numbers of patients in different age ranges within a geriatric ward

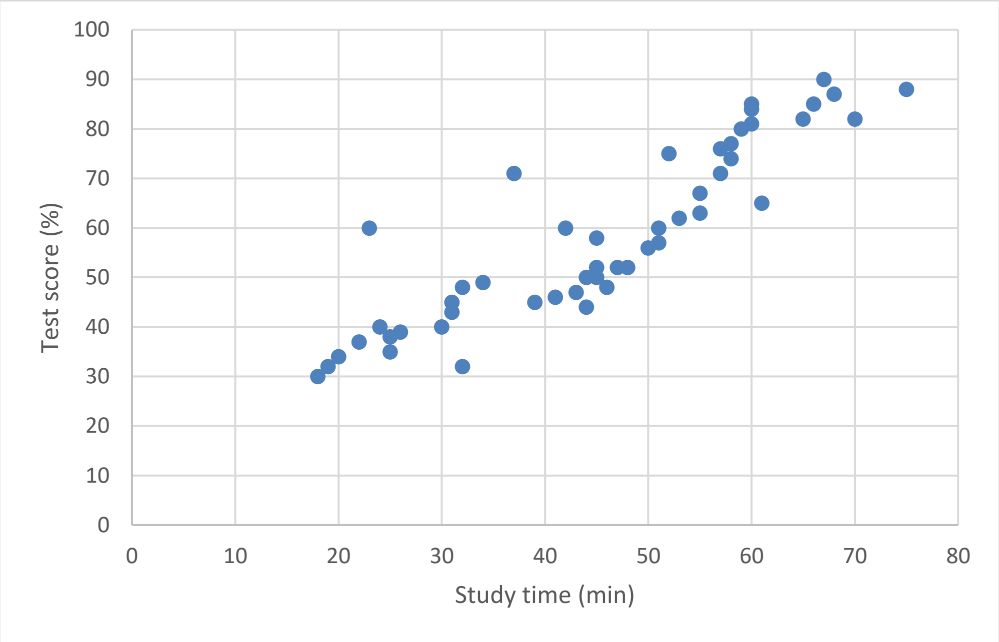


In a bar chart (and also in scatter plots or graphs as in Figure 4), once again a title is required, and also labels for each of the axes (ie. both the vertical, or 'y' axis, and the horizontal, or 'x' axis). Relevant units need to be included on axis labels

The descriptive statistics described above (measures and charts) can be used for all types of data, all sample sizes, and all types of research design. Even with categorical data such as eye colour, you could calculate the mean number of people in a sample who have blue eyes, and you could certainly produce a pie chart or bar chart to show the proportion or actual number of people with different eye colours.

If your data includes two scale variables, you could use a scatter plot to show the extent of any relationship between them, as in Figure 4.

Figure 4: Scatter Plot to show the relationship between time studied and mark obtained in a cohort of 50 first year undergraduates



Note that in scatter plots, the **independent variable** (ie. the variable that doesn't depend on anything, often 'time') is *always* plotted on the horizontal axis, and values of the **dependent variable** (whose values depends on the independent variable) are *always* plotted on the vertical axis. A 'line of best fit' (or regression line) can also be readily added in if required to show the trend in the relationship more clearly (we will focus on straight lines, but they could be curved).

Example: *Ceri, a car sales executive*

Research Question: "What are the car purchase preferences of the residents of town B?"

Research Design (and Method): *Survey* to all residents of town B to obtain information on car preferences, with both qualitative questions (eg. on car colour and type), and quantitative questions (eg. numerical rating of car performance).

Descriptive analyses: pie chart to show % colour preferences; bar chart to show numbers of cars of different makes purchased; table to show, per type of car, cost range, mean age of purchaser, mean annual mileage, modal colour

Inferential Statistics

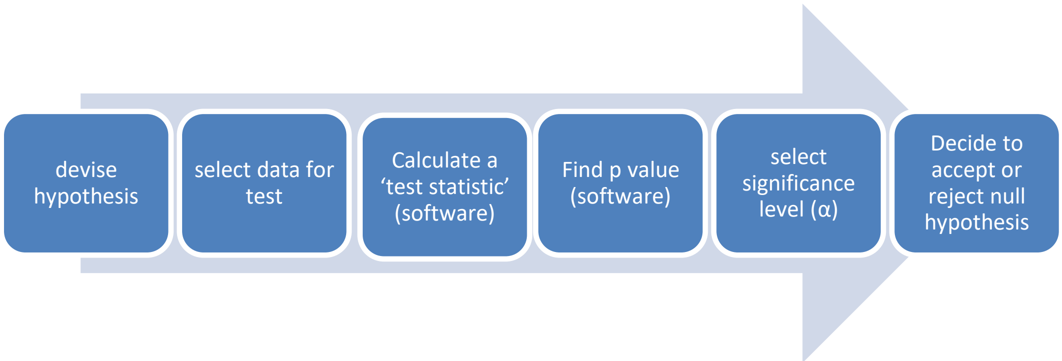
Inferential statistics - or statistical tests – *infer* relationships or differences in a population based on sample statistics. But note that these tests don't give absolute answers; they just indicate how probable it is (or likely) that a relationship or a difference exists. In general, scale data are needed for statistical tests, and you should have a confirmatory research design in which there is an underlying **hypothesis** (or idea). Take the example of a research question which asks if a particular training course improves the skill set of participants. This research question has within it the idea, or implication, that the training course might well improve skills. The research carried out would then aim to confirm this (the research design here would probably be a quasi-experiment). Note that you can't really infer much about a population if you only have a small sample, so fairly large samples are needed for inferential statistics (see the earlier section on Surveys about more detail on sample size).

Statistical tests and p values

Most statistical tests follow the sequence indicated in Figure 4. Depending on your research question and the data you have, you might decide to carry out just one test, or several different tests as part of your data analysis. Your software does all the hard work: you are mostly just looking for a '**p value'** and using this to decide what to infer.

The type of statistical tests carried out, and their outputs, are generally reported in the 'Results' section, after summary data and any descriptive analyses.

Figure 4: process of carrying out a statistical test



The following sections provide more information on each of these steps:

1. **Devise a hypothesis:**

Actually, there need to be *two* hypotheses:

- The '**null' hypothesis**: there is no significant difference or relationship
- The **'alternate' hypothesis**: there is a significant difference or relationship.

As we'll see shortly, at the end of any statistical test we will either accept or reject each of these two hypotheses.

2. Select data for the test

Generally, you need data from a large number of individual people/instances/items (ie. 'raw' data) in a statistical test. You may not need to use all your data for a specific test, so you need to take care when selecting and entering your data into the software package employed. Most software packages require different participants/individuals on different rows, and different variables in different columns.

You will need to refer to specific guides for the package you intend to use, and you may find that watching videos is helpful.

3. Calculate a test statistic

Statistical tests are based on the calculation of a 'test statistic' such as 'T', 'F', or 'Y^2'. All the calculation is done by your software (examples currently popular are IBM's 'SPSS' and Microsoft's 'Excel'), and so these days there is no need to know or understand any statistical formulae. You will, however, need to know how to use your software.

Table 4 shows some of the main statistical tests used with scale data.

4. Find p values

The output of most statistical tests usually involves a table with many different numbers. As a general rule, the only number you need to look for, and report in your 'Results', is the '**p value'**. 'P' stands for 'probability' (specifically, the probability of 'atypical' results even though the null hypothesis is correct). Values of p typically range from just under 1 (eg. 0.953) to really small numbers (such as 0.00000953). Don't forget that the greater the number of zeros behind the decimal point, the smaller the number. Interpretation of the p value obtained depends on the significance level chosen, as explained in the next section.

Note that p values are frequently misinterpreted, so much so that some academic journals have banned their use. Hence, you should take great care when working with p values and get help if you are unsure how to interpret them.

5. Selecting the significance level

The significance level (or α) is the level at which we decide if a p value is significant or not. The usual significance level selected is **0.05** or **5%**. This means, in effect, that we are looking to see if our sample data belongs within the 5% at the extreme edges of a distribution of values, which we consider to be not really part of the population in question (and which gives atypical results due to the null hypothesis not being correct).

To illustrate this in practice, imagine a class of children of roughly the same age. Most (95%, or 0.95) will have heights not far removed from the mean height of the class. But a few children (5%, or 0.05) may be a lot taller or shorter than this. In fact, if you weren't sure about their ages, you might think that they came from a completely different class (or population), either older, or younger. Inferential statistics work in a similar way: if a p value produced by a statistical test is very small (less than 0.05), it looks as if the sample may well have come from a different population. Put another way, the probability of the sample coming from the population being examined is less than 0.05 (more precisely, the probability of such a sample resulting from a correct null hypothesis is less than 0.05).

The use of the 0.05 significance level gives us a cut-off: p values larger than 0.05 put our sample data in with 95% of the population, but p values smaller than 0.05 imply that out sample data is **significantly different** from the population. Hence, most researchers pounce on the p value, and look to see if it is greater or less than 0.05. In general, the smaller the p value, the more significant the result is likely to be. Significance levels of 0.01 and 0.001 can also be used, and if the p value from a statistical test is smaller than these, this suggests an even higher probability of a significant difference or relationship.

6. Accepting or Rejecting the Null hypothesis

The last step in a statistical test involves accepting or rejecting the two hypotheses we devised at the start.

If the p value produced is smaller than 0.05, researchers would normally assume that they have found something significant. They would therefore reject the null hypothesis and accept the alternate hypothesis. If, however, the p value is larger than 0.05, they would need to accept the null hypothesis and reject the alternate hypothesis. Either outcome provides valuable information that researchers can interpret and discuss in the 'Discussion' section of their ultimate report. Note that it is an accepted convention to provide statements on the null and alternate hypotheses at the end of each statistical test (within the 'Results' or 'Analysis' section).

Which statistical test(s) should you use?

That depends on your research question, and you should aim to decide which statistical tests you will use as part of your Research Design, before your start your research.

Table 4 summarises some of the tests that are commonly used in quantitative research in the social sciences:

Table 4: An outline of some key statistical tests

Type of Research question	**Example of Research Question**	**What sort of test is needed?**	**Name of Statistical test**
Is there an association between two categorical variables?	Are management jobs in an organisation associated with one particular gender?	A test that will handle categorical variables	Chi squared (Y^2) test
Is there a relationship between two scale variables?	Is the age of insurance sales staff linked to their revenue?	A test that looks for a relationship (effectively putting numbers to a line of best fit)	correlation and/or regression
Is there a difference (in a scale variable) between two separate groups?	Are reading scores higher in children adopting a new reading method compare to the existing method?	A test that looks for a difference between two *separate* groups	Independent T test
Is there a difference (in a scale variable) in the same individuals at two different times/conditions	Is the leadership rating of managers the same before and after coaching?	A test that looks for a difference between two *linked* groups	Paired T test
Is there a difference (in a scale variable) between more than two groups?	Does patient length of stay differ in five hospital wards with different visiting hours?	A test that looks for a difference between *more than two* separate groups	ANOVA ('Analysis of Variance')
Is there an underlying variable influencing other measured variables?	Could a range of survey responses on a new community initiative be explained by one or two key factors?	A statistical technique that finds the factors (variables) with the greatest correlation coefficients	Factor analysis

Further information on the Chi-squared test

The Chi Squared test is very useful because it can be used for categorical variables, relatively small samples, and data that are not normally distributed (more on that below). This test basically looks for links and differences between observed and expected values.

For example, the data in Table 3 on management roles at different sites might have been generated by a researcher wishing to know if the distribution of management-related staff at three sites of the same firm was about equal. The underlying notion of equal distribution here supplies the null hypothesis stating that there is no significant difference. The alternate hypothesis would state that there is a significant difference in the numbers of people in different management categories at the three sites, with an inferred association between certain management categories and certain sites.

A Chi squared test on these data would compare the recorded numbers per management category at each site (the 'observed' data) with the numbers expected if there were no differences in the categories (the 'expected' data). If the resulting p value is greater than 0.05, you would accept the null hypothesis. If $p < 0.05$, you would reject the null hypothesis, accept the alternate hypothesis, and decide that there are differences in the distribution of management categories at the three sites, with the further inference that there is an association between certain management categories and certain sites.

Further information on Correlation and regression

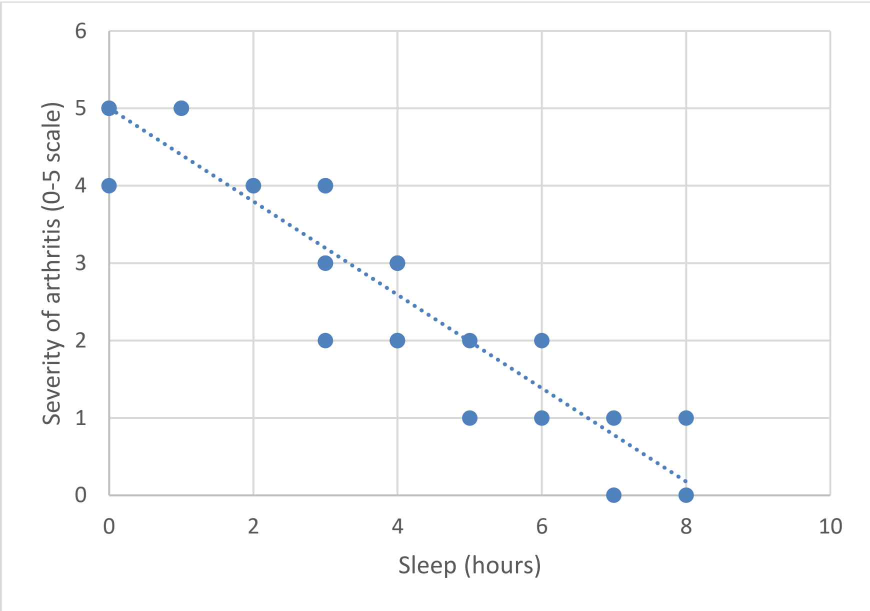
These terms refer to the relationship between two scale variables which can be represented by a straight line (the line of best fit, or trendline) as in the scatter plot in Figure 4.

A number called the '**correlation coefficient'** (sometimes referred to as 'r') indicates how closely the two variables are linked (in terms of the line of best fit) and has values from +1 to -1. If a correlation coefficient is +1, this means that as the value of the independent variable increases, the dependent variable increases in proportion, exactly following the line of best fit. But if the correlation coefficient is -1, then as the value of the independent variable increases, the dependent variable *decreases* (so the line of best fits goes downwards rather than upwards).

Regression analysis provides further information about the line of best fit, and also indicates, via the usual p value, whether the relationship between the variables is significant.

What should we infer from a correlation coefficient close to +1 or -1 which turns out to be significant? To answer this, think about the following completely fictitious example of a study of the sleeping habits of a group of 25 arthritis sufferers:

Figure 5: Scatter plot to show the relationship between hours of sleep and the severity of arthritis



Regression analysis of these data produced a correlation coefficient of -0.85 which was highly significant ($p<0.001$).

Could we infer that *all* arthritis suffers would show the same sort of trend? No: we can only suggest from this small sample that the population of arthritis sufferers *may* show a similar trend.

Could we infer that having very little sleep worsens arthritis symptoms? No: it's never good to use correlation to infer 'cause and effect'. If the scatter plot was the other way around, with severity of arthritis as the independent variable, you might infer that the worse the arthritis, the less sleep you get (which is not unreasonable). The correlation coefficient would be the same in either case.

All we can infer here is that in this sample, there was a strong negative relationship between sleep levels and the severity of arthritis. This might prompt the researchers involved to carry out a more extensive and precise study.

Further information on Factor Analysis

Factor analysis is appropriate when many different variables, or factors, are involved, as in a survey. Each question in a survey constitutes a factor in participants' overall views of the survey topic. During factor analyses, all the factors are compared using correlation. The highest correlation coefficients (ie. closest to +1 or -1) are assumed to indicate the main factors involved. This process helps to reduce the number of factors that researchers need to focus on, and points to potential underlying factors that could be responsible for the results obtained. Factor analysis needs to be carried out by suitable software such as SPSS (see Field, 2013).

Non-parametric statistical tests

The statistical tests in Table 4 are described as '**parametric**', meaning that they are based on an assumed set of population parameters, one of which is that the data follow a 'normal distribution' (ie. a distribution that looks like a bell-shaped curve with most values in the centre, and fewer at the edges). These tests generally require scale data (and large samples). Ordinal data, as produced from questionnaires, are best analysed using '**non-parametric'** variants of these tests, as listed in Table 5. As mentioned above, however, the Chi squared test will handle categorical variables, relatively small samples, and data that are not normally distributed.

Table 5: Parametric and non-parametric statistical tests

Parametric statistical test	Non-parametric equivalent
Independent T test	Mann-Whitney test
Paired T test	Wilcoxon test
Analysis of variance (ANOVA)	Kruskal-Wallis test
Pearson correlation	Spearman correlation

Example: *Nasreena, a community sports coach*

Research Question: "Do vitamin supplements affect performance in novice older runners?"

Research design: quasi-experimental, with non-random selection of participants who act as their own controls (sometimes referred to as a 'single subject' design).

Research Methods: Measurement of time taken to run an appropriate distance in a large group of runners before and after taking vitamins for a suitable time period (pre- and post-test measurements).

Descriptive analysis: Table to show means and standard deviations of times to run 100m before and after taking the vitamins

Inferential analysis: Paired T test to look for any significant difference in the before and after times *in the same individuals*

[Note that in a true experimental design, as many variables as possible would be controlled, eg. other supplements taken, amount of training, weather during running. But in her community context, Nasreena might only manage to control dosage and time period for taking the vitamins. Her research therefore has several limitations, but could be a starting point for a more rigorous study]

For more information on statistical tests try:

- Bluman, A. (2013) *Elementary Statistics: A Step By Step Approach*. New York: McGraw-Hill Education
- Field, A. (2013) *Discovering Statistics Using SPSS: (and Sex, Drugs and Rock 'n' Roll)*. 4th ed. Los Angeles: SAGE.

Additional points on quantitative analysis

Researchers may additionally need to report on measures such as validity, reliability and effect size.

Validity refers to whether a particular measure actually assesses what it is meant to assess. For example, is a questionnaire question on 'length of lunch-break' a valid measure of job satisfaction?

Reliability, by contrast, gives an indication of the repeatability of results. This is often discussed in the context of questionnaires: for example, would the same person answer the same question the same way on two different occasions? Reliability can be gauged using a measure called 'Cronbach's Alpha', and this is discussed thoroughly by Field (2013).

Effect Size indicates the strength of the relationship between specific scale variables. It can be thought of as another term for 'correlation', though there are other values that can indicate Effect Size, such as 'Cohen's d'. Once again, Field (2013) is also a good source for information on this.

Example: *Danni, a sociology Master's student*

Research question: how does household income affect school attendance of 15-year olds in a certain city?

Research design: Mixed methods

Research methods: survey; examination of attendance data (secondary data); interviews

Descriptive analysis: summary table to show mean attendance of 15-year-olds in different income groups (eg. 5 groups); scatter plot to show relationship between income (independent variable, horizontal axis), and attendance (dependent variable, vertical axis).

Inferential analysis: correlation/regression analysis to gauge the relationship between income and attendance; associated effect size; ANOVA to look for differences in attendance between the 5 income groups

Section 7: Discussing your Results

Obtaining data, and completing data analysis, are important milestones in the research process. But your research is not complete until you have thought about the inferences your results provide. In the 'Discussion' section of your report /article/dissertation, you need to consider your results in the light of pre-existing research. Do your results follow trends observed by other researchers? Have you produced new knowledge? Will the outcomes of your research improve practice? You should aim to summarise your conclusions at the end of this section, and also acknowledge limitations, and make suggestions for future research.

A word of advice before you start to write up any of your work, based on the recommendations of the Open University (https://help.open.ac.uk/academic-writing-style): aim for the 'three Cs' of **Clarity**, **Coherence**, and **Conciseness**. In other words, be clear about your message, write logically with related points following one another, and aim to be brief. If you need to use technical language, explain it, and don't use long words unless you need to. Make sure, also, that you adhere to the rules of the referencing system you need to use (eg. Harvard), whether for in-text references, your reference list, quotations, footnotes, or any other additionalities in your text. Referencing software can help with this, but you need to check its output and amend if necessary.

More information on writing up research:

Göpferich, S. and Neumann, I. (2016) *Developing and Assessing Academic and Professional Writing Skills*. Peter Lang International Academic Group.

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