If the new exercise regime was effective Chris might expect to find a difference in the stamina levels between the two groups in the post-test. She might expect to find that experimental Group A have more stamina. She would then statistically test her measures of stamina to determine whether this was the case. Different subject design is illustrated diagrammatically in *Figure 4*.

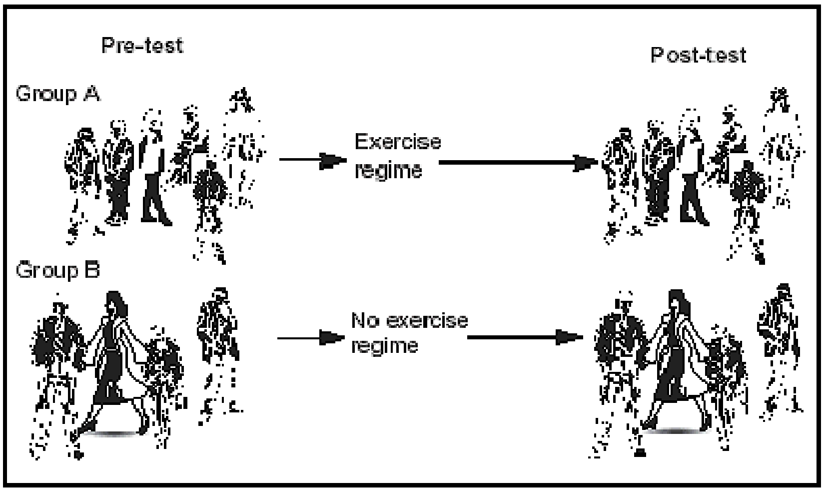

Figure 4: *Illustration of different subject design*

Matched subject design

This approach is a refinement of the different subject design approach. As the title implies, it involves two or more groups of subjects who are matched on factors that could bias the results. For example, Chris might recognise that if she is to undertake a study into fitness she needs to consider factors such as gender, age, height and weight, as these are all factors that could have an impact on stamina levels. To find a matched sample group the researcher will need to make a list of criteria and select participants for allocation to specific groups on the basis of matching against the stated criteria. For example, Chris may decide to match the sample in each group so that there are equal numbers of people within a stated gender, age, height and weight range. As with the previous approaches, each subject takes part in one condition only. People in Group A will have the new exercise regime, and Group B the normal routine (see *Figure 5*).

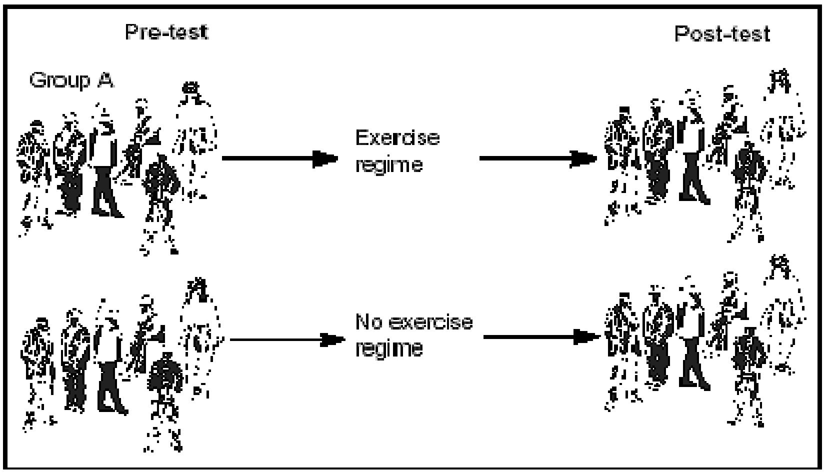

Figure 5: *Illustration of matched subject design*

The importance of subject design

When a researcher is planning an *experimental* research study what he or she wants to find out is whether the hypothesis can be supported. The researcher is more likely to be able to state with confidence that a hypothesis can be supported if the study fulfils the criteria for an experimental research project, namely, that the researcher:

- manipulates the independent variable
- controls the situation
- selects a random sample.

In addition there would be stronger support if the results from the experimental group are compared with a control group.

Where statistical analysis is concerned, same and matched designs are treated as the same thing, whilst different subject designs are put through a different set of analytic procedures. The reason for this is that same subject design is really a perfectly matched sample. If you wanted to see how a group of people responded to a new experience and sought to gather data about that group before and after the new experience, you could assume that any changes noted were due to the new experience because the same group is being tested twice. In using the same subjects to test a hypothesis you have got a perfect match – which is what you are trying to achieve when choosing a matched sample. In contrast to this, the findings from a different subject design could be distorted by a variety of factors such as age, education or different life experiences.

When deciding how to analyse the data from a research design, then, we need to start by establishing where we have a same, different or matched subject design. Building a decision chart like the one in *Figure 6* will help us decide ultimately which statistical test to carry out. We will be adding to this chart as we continue through this session.

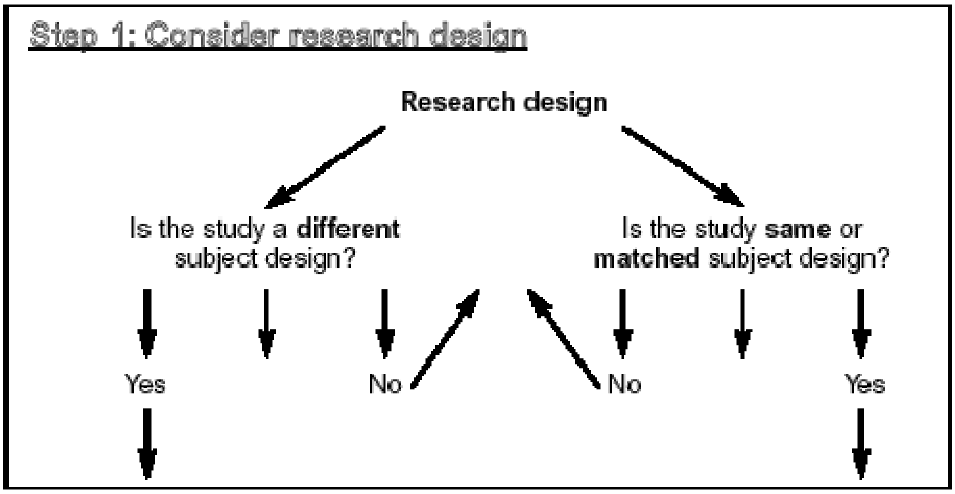

Figure 6: *Step 1 in a decision chart for statistical testing*

We now need to move on to consider the next important issue that may influence our choice of statistical test – the type of data we collect.

2: Classifying the data

We will now spend a little time considering the way in which we collect data because it is another essential principle in understanding statistical testing. Let us imagine we are doing a study of the type of housing people live in. We have circulated a questionnaire that starts by collecting a range of biographical data, as shown in *Figure 7*.


Gender:

Occupation:

Housing:

Figure 7: *Details requested in a questionnaire on housing*

The data collected here fall into named categories:

- *gender* will obviously be male/female

- the *occupation* can be varied but, eventually, as we collect data from many sources, could be subsumed into common named categories such as 'white collar worker' or 'manual worker'

- the *housing* categories can be named, for example, 'owner occupier', 'tenant renting'.

Named data of this type is known as **nominal data** – that which can be grouped into named categories.

Nominal data: *data that can be grouped into named categories.*

Another category of data enables responses or observations to be ordered in some way. For example, we might want to rank from least to most, or from best to worst. As this is a way of ordering data for the purpose of identifying patterns in response it is known as **ordinal data**. This type of data is like nominal data in that named categories may be used, but information can be ordered. Take, as an example, people's attitudes towards a particular statement concerning the National Health Service: 'Health care services have been much improved in the last ten years'. Those questioned may either 'strongly agree', 'agree', 'have no opinion', 'disagree' or 'strongly disagree' with the given statement. Even though there are different categories, they can be placed in some sort of order from strong agreement through to strong disagreement.

Ordinal data: *data that may be allocated to named categories but may be 'ordered', for example, from least to strongest (e.g. strongly agree to disagree).*

A popular means of implementing an ordinal scale is to designate a number to each of the groups, so that 1 = strongly agree, 2 = agree, 3 = have no opinion, and so on. The distance between the various points, however, is not necessarily the same. For example, the difference between 1 and 2 may not be the same as that between 2 and 3. Although indicating stronger feeling, a respondent who strongly agrees, for example, will not be agreeing twice as much as one who has simply agreed with a statement.

Interval measures are measures that have an equal distance between them but lack a non-arbitrary zero point. For example, measures of human performance such as test results, intelligence quotient or personality inventories produce statistics that can be measured against an interval scale. If subject A achieves a score of 100 on an IQ test, subject B 120 and subject C 135, then by implication we can state that subject A is less intelligent than subject B who is less intelligent than subject C. We can plot these results on an interval scale between, say, 0-140. What we cannot do is be absolute about differences in the intelligence quotient of each subject because the full range of abilities has not been tested.

Ratio measures are more refined because absolute measures are valid. For example, someone who is 60 years old has lived twice as long as someone who is 30 years old. We can be non-arbitrary about this in a way that is not possible with measurement of IQ. This is a property that applies only to ratio scales.

Although a difference between the two measures are noted you will see in the context of the statistical tests examined in this text that interval/ratio data are grouped together when used.

Now we have explored the ways in which subjects can be allocated to groups in research and considered the types of data we may collect, we can develop the next step in our decision chart that will help us to decide which statistical test to use – see *Figure 8*.

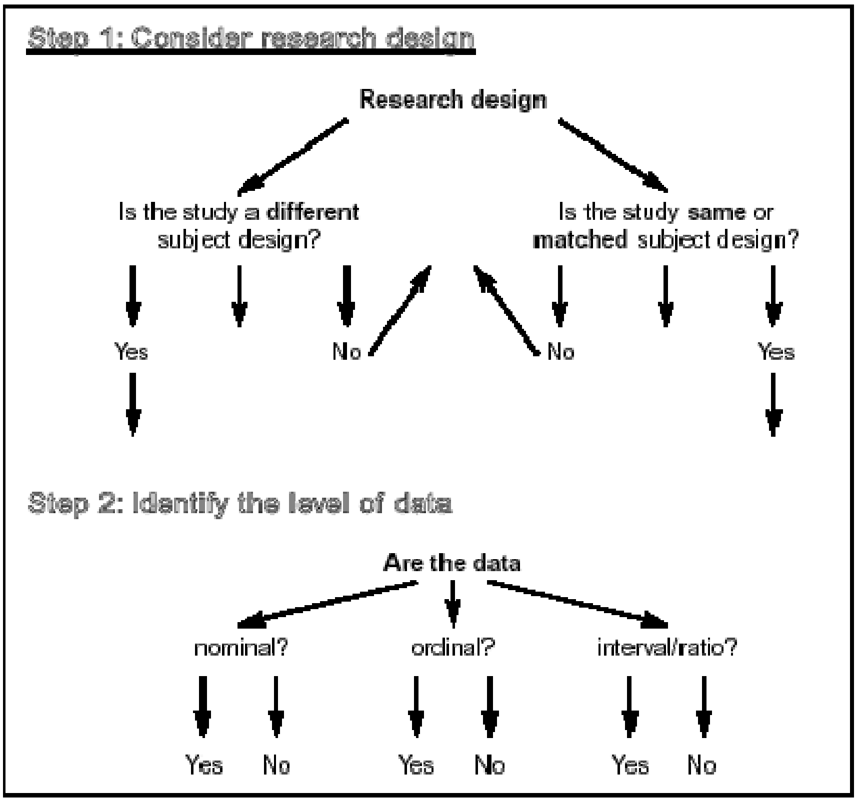

Figure 8: *Step 2 added to a decision chart for statistical testing*