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Quantitative Data Analysis: Types, Methods and Examples

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Abstract

Quantitative data analysis turns numerical data into answers to research questions, but a test applied to data that cannot support it produces results that look sound and support little. This article introduces the two branches of quantitative analysis: descriptive statistics, which summarize the sample that was measured, and inferential statistics, which use that sample to draw conclusions about a wider population. It defines the common descriptive measures and works through them on a small data set, then describes common inferential tests: t-tests, analysis of variance, chi-square tests, correlation and regression. Extracts from three doctoral studies show how descriptive results, inferential results and the choice of non-parametric tests are reported and justified. The article then sets out the two factors that guide the choice of method (the type and shape of the data, and the research questions) and summarizes the choice in a table and a decision flowchart. It is intended for students and early-career researchers planning or reporting a quantitative analysis, and for the educators who teach research methods and statistics.

Keywords: quantitative data analysis; quantitative data analysis methods; types of quantitative analysis; descriptive statistics; inferential statistics; choosing a statistical test; parametric and non-parametric tests; open educational resource

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1. Introduction

Quantitative analysis is the stage at which many otherwise well-designed studies run into difficulty. The statistics themselves are rarely the obstacle. The harder task is deciding which statistics to use and justifying that choice, because a test run on data it cannot support yields results that will not withstand an examiner's or reviewer's first question, however carefully the data were collected.

This article is written for students and researchers making that decision and for those who teach it. Section 2 defines quantitative data analysis and the purposes it serves. Section 3 introduces the distinction between a sample and a population, on which the two branches of quantitative analysis rest. Section 4 covers descriptive statistics and Section 5 inferential statistics, each with an extract from a doctoral study showing how results are reported. Section 6 sets out how the type and shape of the data and the research questions together guide the choice of method, with a third extract showing how the choice of non-parametric tests is justified.

2. What Quantitative Data Analysis Is

Quantitative data analysis is the analysis of **data that are numerical**, or that can be converted into numbers without losing their meaning. Categorical variables (variables whose values are categories), such as gender, ethnicity or native language, can be coded as numbers (English = 1, French = 2, and so on) without losing any information; the numbers act only as labels. Qualitative data analysis, by contrast, works with words, phrases and expressions that cannot be reduced to numbers.

Quantitative analysis generally serves one or more of three purposes (Figure 1): testing whether groups differ, testing whether variables are related, and testing whether the evidence supports a stated prediction.



Figure 1. Three purposes of quantitative analysis, with an example question and typical tests.

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Whatever the purpose, the work is done with statistics: basic calculations such as averages and medians, and more involved analyses such as correlation and regression.

3. The Two Branches: Sample and Population

The statistical methods used in quantitative analysis fall into two broad branches: **descriptive statistics**, which describe the data, and **inferential statistics**, which draw conclusions about more general situations beyond the data actually collected (Guetterman, 2019). Depending on its research questions, a study may use only descriptive statistics or both.

The difference between the branches rests on two terms: population and sample. The **population** is the entire group of people, organizations or other units that a study is interested in. A study of Tesla owners in the United States, for example, has every Tesla owner in the United States as its population. It is rarely possible to survey or interview every member of a population; a researcher might realistically reach a few hundred or a few thousand through an online survey. This smaller group, whose data are actually collected, is the **sample**. Inferential statistics are valuable when it is not possible to examine every member of a population (Ali & Bhaskar, 2016).

Figure 2 places the two branches side by side, with the Tesla example: descriptive statistics stay with the 500 people surveyed, and inferential statistics reach from them to every Tesla owner in the country.

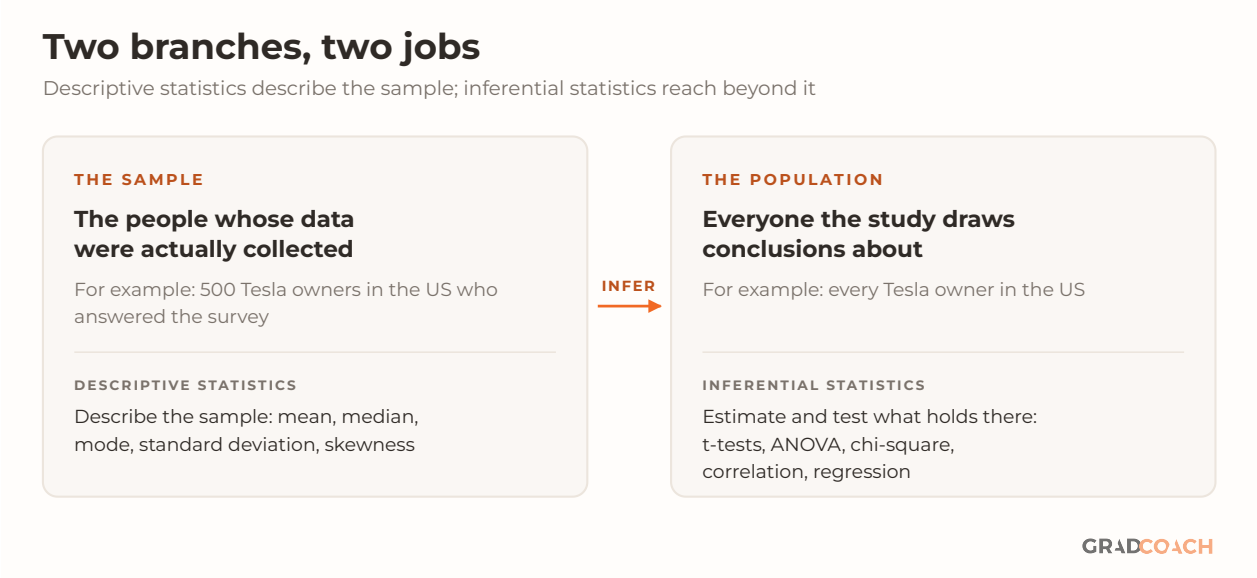

Figure 2. Descriptive statistics describe the sample; inferential statistics reach beyond it.

4. Descriptive Statistics

Descriptive statistics summarize a data set by its typical values and the spread of values for each variable (Guetterman, 2019). They make no claim about the wider population. In a write-up they come before any inferential statistics, and depending on the research questions they may be the only statistics a study needs. A research question that asks only how satisfied the students in a survey are with online lectures, for example, may be answered completely by means and percentages.

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The most common descriptive measures, though not the only ones, are the following:

1. **Mean:** the arithmetic average, the total of the values divided by their number.
2. **Median:** the middle value when the values are ranked, with half above it and half below (Ali & Bhaskar, 2016). With an odd number of values it is the middle value; with an even number it is halfway between the two middle values.
3. **Mode:** the value that occurs most often (Ali & Bhaskar, 2016).
4. **Standard deviation:** how widely the values are spread around the mean. It is low when most values lie close to the mean and high when they are widely scattered. It is the square root of the variance (Ali & Bhaskar, 2016).
5. **Skewness:** how symmetrical the values are, that is, whether they are spread evenly on both sides of the center, or trail off further to the left or the right.

Table 1 gives a small illustrative data set: the body weight of ten people. Table 2 gives the descriptive statistics for these weights, with the Microsoft Excel function that calculates each one.

Table 1. Body weight of ten people (illustrative data).

Person	1	2	3	4	5	6	7	8	9	10
Weight (kg)	70	55	90	75	66	73	80	58	76	81

Table 2. Descriptive statistics for the data in Table 1, with the Excel function for each.

Statistic	Result	Excel function
Mean	72.4 kg	=AVERAGE
Median	74 kg	=MEDIAN
Standard deviation	10.6 kg	=STDEV.S
Variance	113.2 kg^2	=VAR.S
Skewness	−0.22	=SKEW

The mean weight is 72.4 kg. The median (74 kg) lies a little above the mean, because the two lowest weights (55 and 58 kg) pull the average down. The skewness of −0.22 points the same way: the data are **slightly negatively skewed**, with a longer tail toward the lower values. There is no mode, because every weight occurs only once; had two people each weighed 65 kg, the mode would be 65. The standard deviation of 10.6 kg reflects a fairly wide spread, with weights running from 55 to 90 kg. The variance (113.2) is the standard deviation squared and so carries the same information in squared units. Ten records is a very small data set, so little can be read into these figures.

Although descriptive statistics are simple, they have three uses. First, they give both an overall and a detailed view of the data. Second, they help to **detect errors** before further analysis (Guetterman, 2019): a mean far higher than expected, or widely varied answers to a single question, is a reason to check the data. Third, they show **which inferential tests the data can support**, because many of those tests depend on the shape of the data. Guetterman (2019) accordingly places

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descriptive statistics, and a check of each test's assumptions, before any inferential analysis. Skipping over the descriptive results to reach the inferential tests sooner can lead to flawed findings.

In a thesis or research report, descriptive results are usually accompanied by a sentence stating what they mean. The following extract is from a doctoral dissertation in agricultural sciences education at Purdue University, which surveyed undergraduate students about their sense of belonging using five-point rating scales:

> There were 11 items in part two of the questionnaire to measure students' sense of belonging. Each question was based on a 5-point Likert scale (i.e., 1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree). On average, the overall sense of belonging for all participants was toward "Agree" on the Likert scale (M = 3.87, SD = 0.86). This indicated that participants agreed that they felt a sense of belonging in their current institution.
>
> Huang (2019, p. 91)

The extract follows a clear order: the scale is explained first, then the figures are given (M for mean, SD for standard deviation), and then their meaning is stated in plain words. Reporting descriptive results in this order means the reader never has to interpret a number unaided.

5. Inferential Statistics

Inferential statistics draw conclusions from a sample about a population (Guetterman, 2019): they estimate what would be expected in the full population on the basis of what was observed in the sample. Researchers use them chiefly to examine two things (Guetterman, 2019):

1. **Differences between groups**, such as differences in height between children grouped by their favorite meal.
2. **Relationships between variables**, such as the relationship between body weight and the number of hours a week a person practices yoga.

Inferential statistics are also the tools of **hypothesis testing**: assessing whether the data support a research hypothesis. They do this by asking whether a pattern in the sample is larger than chance variation alone would be likely to produce. The answer is usually expressed as a *p*-value; a result is called statistically significant when the *p*-value falls below a chosen threshold (the significance level), such as .05 (Sullivan & Feinn, 2012).

The composition of the sample matters a great deal for inference. A sample that does not represent the population cannot support conclusions about that population. If a population is 50% men and 50% women but the sample is 80% men, for example, the results cannot simply be generalized from the sample to the population.

5.1 Common inferential tests

There are many inferential methods. Five common ones are the following:

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1. **t-tests** compare the means of two groups to assess whether they differ significantly (Guetterman, 2019): for example, the mean blood pressure of a group that took a new medication and that of a group that did not.
2. **Analysis of variance (ANOVA)** also compares means, but across three or more groups at once. Running several t-tests on pairs of groups instead would raise the overall chance of a false positive (concluding that a difference exists when there is none in the population) above the chosen significance level (Kim, 2014).
3. **Chi-square tests** work with categories rather than numbers. They test whether two categorical variables are associated (Kim, 2017), such as whether preferred brand differs between age groups.
4. **Correlation** measures whether two variables tend to change together (Guetterman, 2019): that is, whether, as one rises, the other tends to rise, fall or show no systematic change. Ice cream sales, for example, seem likely to rise with the average temperature; correlation measures whether, and how strongly, they actually do.
5. **Regression** goes a step further and models how one or more predictor variables relate to an outcome variable (Guetterman, 2019), so that the outcome can be estimated from the predictors.

Neither correlation nor regression can, on its own, establish cause and effect. An observed association does not show that a relationship is causal (Schober et al., 2018); two variables can move together because a third variable drives both. A causal claim therefore depends on the research design, such as a controlled experiment, rather than on the statistic.

Figure 3 illustrates a positive correlation: as height increases, weight tends to increase as well.

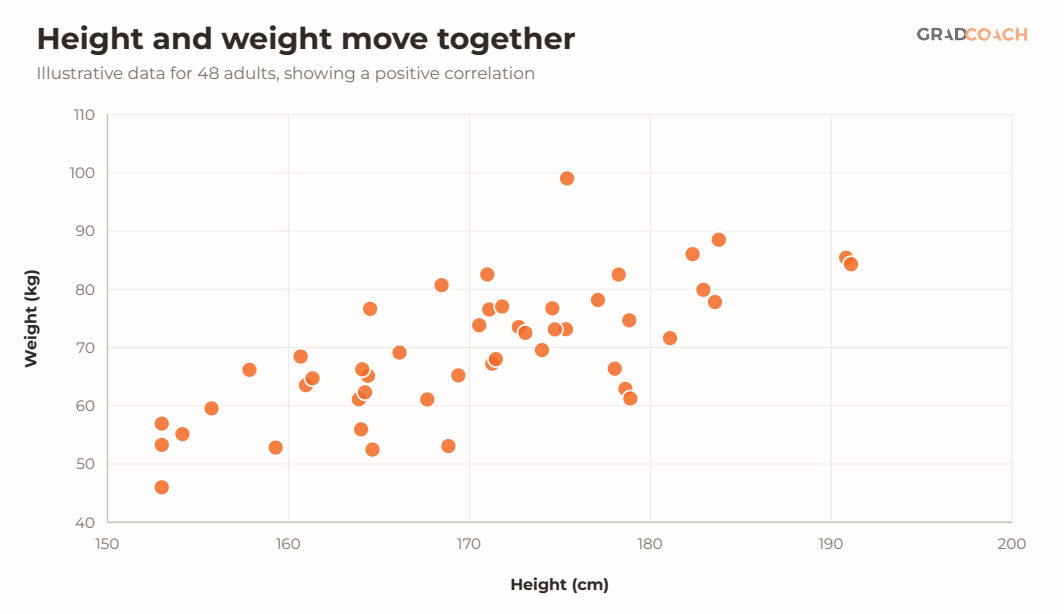

Figure 3. A positive correlation between height and weight (illustrative data for 48 adults).

The points drift upward from left to right, which is the pattern of a positive correlation. The spread of the points around that trend is the reason the relationship is described as a tendency rather than a rule.

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5.2 Reporting inferential results

Inferential results follow a standard pattern in a write-up: the statistic, its significance (a *p*-value or confidence interval), an effect size and a brief written interpretation (Guetterman, 2019). The following extract is from a doctoral dissertation in psychology at Purdue University, which tested whether people recall words better when they generate their own memory cues. After exclusions, 283 participants each studied words under three cue conditions (Fordyce, 2026, pp. 34–35). The analysis first asks whether the conditions differ at all, and then which conditions differ from which:

> A significant difference in the proportion of words correctly recalled was observed between conditions (Figure 4 [in the original]). Performance was best in the generated cue condition and equivalent in the generated descriptive cue condition and allocated cue condition. This was confirmed with a repeated-measures ANOVA, $F(2, 564) = 8.22$, $MSE = .01$, $p < .001$, $\eta_p^2 = .03$. Performance was significantly higher for the generated cue condition relative to the allocated cue condition, $t(281) = 4.00$, $p < .001$, and relative to the generated descriptive cue condition, $t(281) = 2.88$, $p = .004$. However, there were no significant differences in performance between the generated descriptive cue condition and the allocated cue condition, $t(281) = 1.40$, $p = .171$.
>
> Fordyce (2026, p. 42)

The ANOVA answers whether there is any difference among the three conditions, and the t-tests then identify which pairs differ. These follow-up tests are themselves multiple comparisons, so they are usually adjusted, for example with a Bonferroni correction, which divides the significance level by the number of comparisons (Kim, 2014). For three pairs the threshold becomes $.05/3 \approx .017$, and both significant results reported here ($p < .001$ and $p = .004$) fall below it.

The same participants took part in all three conditions, so the ANOVA is a **repeated-measures** ANOVA, the form used when the same people are measured under several conditions; a standard ANOVA would ignore the correlation between repeated measurements of the same person (Ali & Bhaskar, 2016).

The value η_p^2 (partial eta squared) at the end of the ANOVA result is an **effect size**: it shows how large the difference is. A *p*-value can indicate whether an effect exists but does not reveal its size, so both should be reported (Sullivan & Feinn, 2012). The extract also states each result in words before giving the numbers that support it, an order that suits any results section.

Every inferential test rests on assumptions, such as normally distributed data (values that form a symmetrical, bell-shaped curve) and independent observations (observations unrelated to one another, so that, for example, no person is measured twice) (Guetterman, 2019). **Parametric tests**, such as the t-test and ANOVA, assume numerical data with an approximately normal distribution; **non-parametric tests** do not require that assumption and are used for ordinal data (ordered categories, such as low, medium and high) and for numerical data that are skewed (Ali & Bhaskar, 2016). Checking the descriptive statistics first, as Section 4 recommends, shows whether the normality assumption is plausible; independence depends on how the data were collected.

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6. Choosing an Analysis Method

The choice of statistical methods depends on two factors: the **type and shape of the data**, and the **research questions and hypotheses**. Sections 6.1 and 6.2 deal with the data and Section 6.3 with the research questions.

6.1 The type of data

The first consideration is the type of data collected, or to be collected, by which is meant the level of measurement. Stevens (1946) distinguished four levels, nominal, ordinal, interval and ratio, and argued that each permits a different set of statistical operations. Each level keeps the properties of the one below it and adds one more, and the more properties the data have, the wider the range of tests that can be applied (Figure 4).

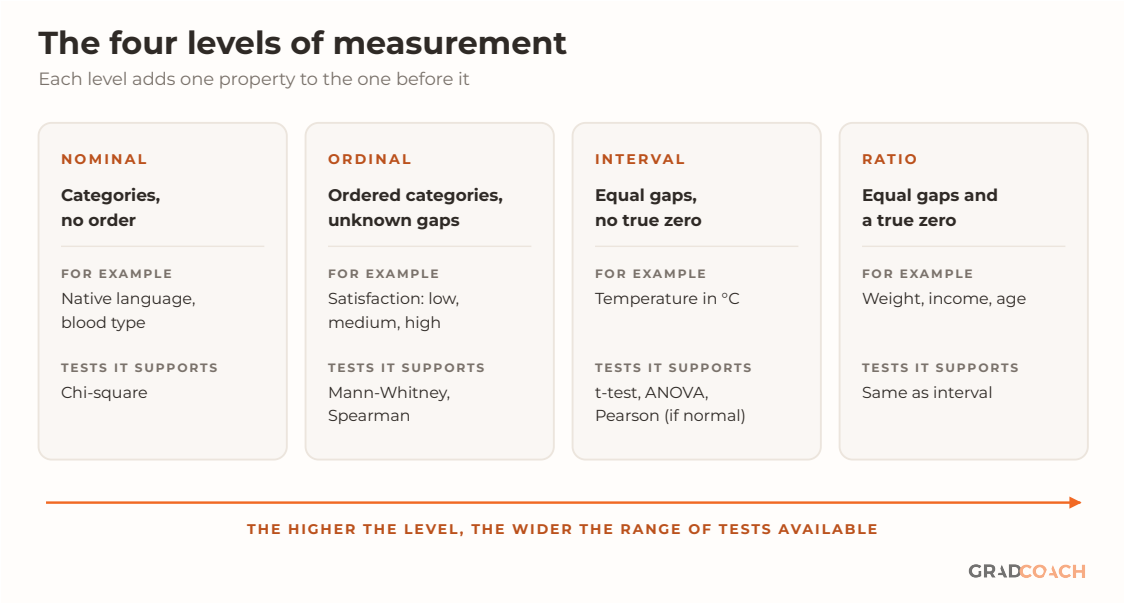

Figure 4. The four levels of measurement, with examples and the tests each typically supports.

The level matters because different statistical methods **require different types of data**. Some work with categorical data, such as yes/no answers, gender or ethnicity; others with continuous numerical data, such as age, weight or income; and some with both. A method applied to a type of data it does not support produces results that are largely meaningless, so each variable's level should be established before a test is chosen. The University of California, Los Angeles, publishes a table matching common tests to the type of outcome variable, the number and kind of groups, and whether the outcome is normally distributed (UCLA Statistical Methods and Data Analytics, n.d.); the table describes its recommendations as general guidelines, not fixed rules.

Where the data have not yet been collected, the planning can run in reverse: decide which analysis would answer the research questions, then design the data collection to produce the data that analysis requires. This keeps the aims, the data and the methods aligned, which is what examiners and reviewers look for.

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6.2 The shape of the data

The second consideration is the **shape of the data**: whether the values are approximately normally distributed, forming a symmetrical bell-shaped curve, or skewed to the left or the right (Figure 5). Parametric tests assume approximately normal data; non-parametric tests are designed for data that are not. In larger samples, however, the t-test and linear regression remain valid even when the outcome is not normally distributed (Lumley et al., 2002). Strictly speaking, the normality assumption applies to the model's errors (the gaps between the observed values and their expected values) rather than to the outcome variable itself (UCLA Statistical Methods and Data Analytics, n.d.). Mild skew alone is therefore not a reason to abandon a parametric test in a large sample.

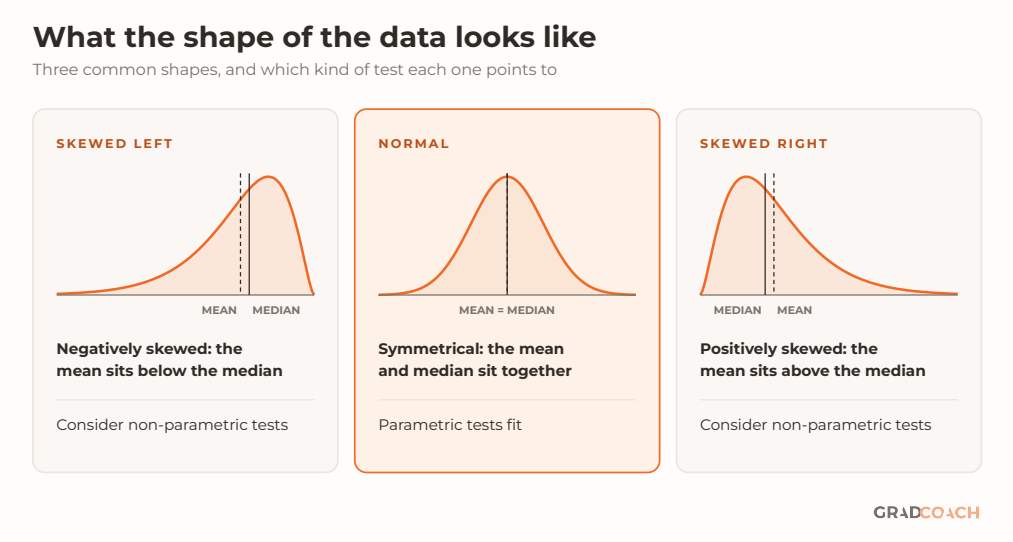

Figure 5. Three common shapes of data and the kind of test each points to.

Descriptive statistics show which shape the data have. A skewness close to zero, with the mean and median close together, suggests a roughly symmetrical distribution; a histogram or a Q-Q plot (which compares the data with the values a normal distribution would produce) shows whether it is also approximately normal. The textbook rule shown in Figure 5, that the mean lies on the side of the longer tail, is only a rule of thumb, however: it often fails in discrete data and in some other distributions (von Hippel, 2005), so skewness and a plot of the data are better guides than the mean and median alone.

Studies that use non-parametric tests should state why. The following extract is from a doctoral dissertation in clinical medicine at the University of Szeged, Hungary, which screened pregnant women for depression with the Edinburgh Postnatal Depression Scale (EPDS) and compared groups of unequal size:

> We used non-parametric tests in the statistical analyses because these methods do not require a normal distribution, thus they are more reliable when the variables are not normally distributed. Also, these tests do not require equal group sizes. These non-parametric tests transform the data (the EPDS scores) in their computations, and their results are mean ranks (instead of EPDS score means).
>
> Hompoth (2020, p. 11)

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The passage names the choice, gives the reason in terms of the **shape of the data**, adds a second reason (unequal group sizes) and tells the reader what form the results will take. The second reason is the weaker of the two. Parametric tests do not require equal group sizes, and where two groups differ in spread (variance), Welch's *t*-test is an established adaptation of the *t*-test (Kim, 2014). With that caveat, a justification for non-parametric tests can follow the same pattern.

6.3 The research questions

The other factor is the research questions, together with any hypotheses. They largely determine which statistical methods are needed. A study that seeks only to describe its **sample** may need nothing beyond descriptive statistics. A study that tests **differences between groups or relationships between variables**, and generalizes to the population, needs inferential statistics as well as descriptive ones.

Table 3 combines the two factors for the most common questions. The middle column assumes numerical, approximately normal data; the right-hand column gives the usual alternative for ordinal or non-normal data (UCLA Statistical Methods and Data Analytics, n.d.).

Table 3. Common questions and the parametric and non-parametric tests that answer them.

Question	Numerical, normal data	Ordinal or non-normal data
Do two separate groups differ?	Independent-samples *t*-test	Mann-Whitney *U* test
Do the same people differ at two points?	Paired *t*-test	Wilcoxon signed-rank test
Do three or more separate groups differ?	One-way ANOVA	Kruskal-Wallis test
Do the same people differ at three or more points?	Repeated-measures ANOVA	Friedman test
Are two variables related?	Pearson correlation	Spearman correlation

For correlation, the Pearson coefficient is typically used for data that are jointly normally distributed, and the Spearman rank coefficient for non-normal continuous data, ordinal data or data with relevant outliers (Schober et al., 2018).

Figure 6 sets out the same decision step by step and adds two cases that Table 3 leaves out: an outcome that is a category, which calls for a chi-square test, and the prediction of an outcome from other variables, which calls for regression. The chi-square test relies on a large-sample approximation; when expected counts are small, Fisher's exact test is used instead (Kim, 2017). The type of regression depends on the outcome: linear regression for a numerical outcome and logistic regression for a categorical one, for example (UCLA Statistical Methods and Data Analytics, n.d.).

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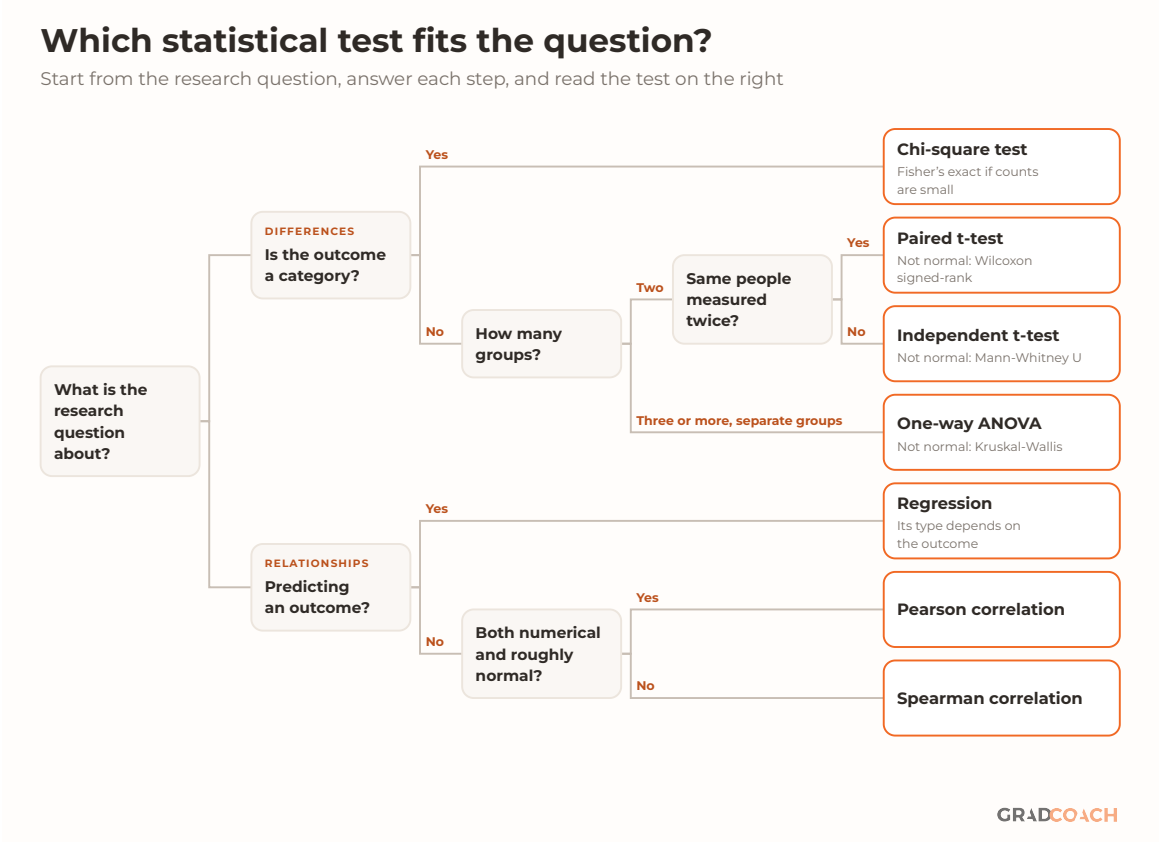

Figure 6. Choosing a statistical test; alternatives cover non-normal data and small counts.

The flowchart covers separate groups and pairs of measurements. When the same people are measured three or more times, as in the psychology study in Section 5.2, the repeated-measures ANOVA takes the place of the one-way ANOVA, with the Friedman test as its non-parametric alternative (Table 3). The chi-square branch likewise assumes independent groups; paired categorical data call for other tests, such as McNemar's test (UCLA Statistical Methods and Data Analytics, n.d.).

Every route through the flowchart starts from the research question, so the research aims, questions and hypotheses should be settled before any statistical technique is chosen. A technique should never be adopted because it is familiar or preferred; the methods must fit both the data and the questions.

7. Conclusion

Quantitative data analysis uses statistics to make sense of numerical data, including categories coded as numbers. It has two branches. Descriptive statistics summarize the sample that was measured, using measures such as the mean, median, mode, standard deviation and skewness; inferential statistics use that sample to draw conclusions about a population, with tests such as t-tests, ANOVA, chi-square tests, correlation and regression. The choice of test depends on the level of measurement and shape of the data and on the research questions, which is why descriptive statistics should be examined before any inferential test is run. Each result is best reported with its statistic, its p-value, an effect size where one is available, and a plain sentence stating what it means. Any departure from the usual choice of test should be justified in the methods section.

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