

An Introduction to Research for Primary Dental Care Clinicians

Part 8: Stage 9. Analysing the Data

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Introduction

This paper, the eighth in the series, will address the ninth stage of a research project suggested in the first paper. The ten suggested stages are:

1. The initial idea (asking a research question).
2. Searching the literature.
3. Refining the research question.
4. Planning the study.
5. Writing a protocol.
6. Obtaining ethics approval and funding.
7. Piloting the project and project management.
8. Collecting data.
9. **Analysing the data.**
10. Writing up and disseminating the results.

The previous paper outlined how to collect data during a research project. The next stage is to analyse the data that have been collected. This paper briefly introduces readers to data analysis and basic statistics. It updates the Faculty of General Dental Practice (UK) research advice sheets: *Introduction to Statistics, Statistics for Research, Testing for Statistical Significance*.

Stage 9. Analysing the Data

This paper is divided into the following sections:

- A. Introduction
- B. Basic concepts
- C. Displaying data

D. Some commonly used statistical tests

E. Qualitative data

F. Software for statistical analysis

G. Suggested further reading

A. Introduction

The first paper in this series¹ was primarily concerned with asking and refining the research question. The previous two papers in the series have dealt with piloting the methodology² and collecting the data;³ the next stage is data analysis. This involves the use of statistics. This paper gives a very brief introduction to statistics. It does not seek to describe more than the basic concepts and some frequently used statistical tests. For more details, readers are referred to the books listed in section G of this paper as suggested further reading.

It cannot be over-emphasised that asking for statistical advice from a specialist healthcare statistician at the outset of the research design is essential, otherwise there is a significant possibility that the type of data collected may not be appropriate for suitable analysis and will not answer the research question. A statistician will advise not only on how to present data and on statistical tests that should be applied to the data but also on the size of the sample (the number of patients, restorations, or procedures, and so on) that will be required for a meaningful study. The sample size must be decided before the study begins, because it will have a major impact on data analysis and the validity of the study. As mentioned in the previous paper,² a pilot study will serve to highlight any problems in examiner calibration, data collection and analysis, so that changes may be made before the full study begins. The design of the pilot study should also be discussed with a statistician.

Data collection using electronic data capture or electronic data entry not only simplifies data entry but also helps to ensure that data are clean and free from spurious entries;³ it also facilitates data entry into statistical software packages. However, care is still needed to avoid error, for example when copying and pasting from a spreadsheet, such as Microsoft Excel, or into statistical software, such as the Statistical Package for Social Sciences (SPSS), because it is possible to paste from, or to, the wrong series of rows or columns.

This paper concentrates on data analysis for quantitative research, which is more familiar to dental researchers and more likely to be undertaken in primary dental care settings. However, qualitative research and some of the challenges that it poses will be briefly discussed towards the end of the paper.

B. Basic concepts

B1. Terminology

Statistics has a jargon of its own, which can cause difficulty to those who are beginners. This section explains some of the commonly used terms, starting with the six very commonly used terms that are defined in Table 1.

Table 1: Very commonly used statistical terms	
Mean	Sum of values divided by the number of values: the arithmetic mean
Median	The middle value when ordered from minimum to maximum*
Mode	The most frequently occurring value
Range	The difference between the smallest and largest values
Quartile	Upper quartile cuts off the highest 25% of values
	Lower quartile cuts off the lowest 25% of values
Interquartile range	The difference between the lowest and highest quartiles
* If the number of values is even, then the arithmetic average of the two middle values is used.	

As explained above, the mean is the average. The median is the middle value. Half the values are higher than the median, and half are lower. The median is a more robust measure of central tendency. Changing a single value will not change the median very much. In contrast, the value of the mean can be strongly affected by a single value that is very low or very high.

B2. Variance and standard deviation

Variance and standard deviation (SD) are also frequently used terms. Variance shows how far values differ (vary) from the mean and is calculated from each value (number). From a mathematical viewpoint, variance is expressed as a square of the value measured, as it will always be positive. However, having a squared value is not always very manageable, so standard deviation, which is the square root of the variance, is used instead.

The SD quantifies variability or scatter among the values in a column. If the data follow a bell-shaped Gaussian distribution, then 68% of the values lie within one SD of the mean (on either side) and 95% of the values lie within two SDs of the mean. The SD is expressed in the same units as the data to which it relates.

B3. Standard error of the mean

The standard error of the mean (SEM) is a measure of the likely discrepancy between the mean calculated from the data that have been collected and the true population mean (which is unknown without an infinite amount of data). The SEM is calculated as the SD divided by the square root of the sample size. By itself, the SEM is difficult to interpret. It is easier to interpret the 95% confidence interval (CI), which is calculated from the SEM.

An assumption is made that the sample mean is the same as the population mean. However, this is unlikely to be the case, so SEM is used to estimate how accurately the population mean is estimated by the sample mean. The formula for calculating standard error is the standard deviation divided by the square root of the number of n , when n is the number of observations made. If the standard error and n are known, then it is also possible to calculate the standard deviation.

Many scientists and clinicians are confused about the difference between the standard deviation (SD) and standard error of the mean (SEM).

- The SD quantifies scatter; that is, how much the values vary from one another.
- The SEM quantifies how accurately you know the true population mean. The SEM gets smaller as samples get larger, simply because the mean of a large sample is likely to be closer to the true mean than is the mean of a small sample.

The SD does not change predictably as you acquire more data. As mentioned above, the SD quantifies the scatter of the data, and increasing the size of the sample does not increase the scatter. The SD might go up or it might go down. You cannot predict. On average, the SD will stay the same as sample size gets larger.

If the scatter is caused by biological variability, the variation should be demonstrated to anyone reading the results. In this case, report the SD rather than the SEM. It is better to show a graph of all data points, or perhaps report the largest and smallest value; there is no reason to only report the mean and SD.

When using an in vitro system with no biological variability, the scatter can only result from experimental imprecision. Because you do not really care about the scatter, the SD is less useful here. Instead, report the SEM to indicate how well the mean has been determined.

B4. Confidence intervals

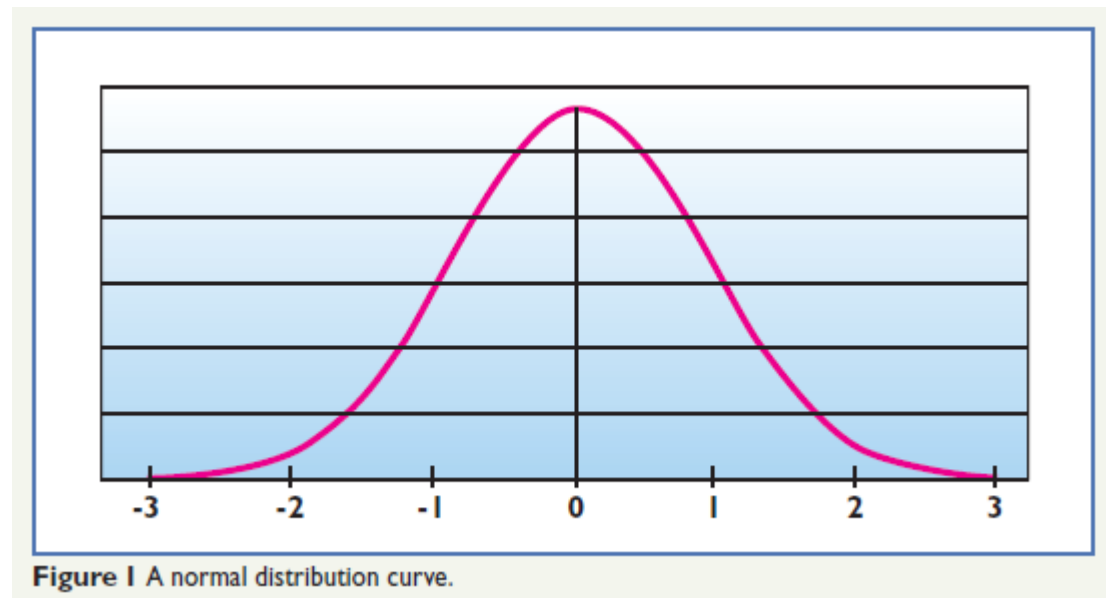
A confidence interval is the reliability of an estimate and allows the sample to be compared to the whole population so that inferences from the sample may be applied to the population. Mathematically, because 1.96 standard deviations, both above and below the mean, contain 95% of the sample mean, it is possible to state that there is a 95% probability that the sample mean lies within 1.96 standard deviations, either above or below, the population mean. Although confidence intervals in dental research are usually expressed at the 95% level, they may also be at 99%. The 95% level is an arbitrary one, which corresponds to a P-value of 0.05; the reasons for this will be considered in the next sections of this paper.

B5. Normal distribution

The normal distribution curve (Figure 1) is often called a bell curve, as it is bell shaped, but could be more properly called after its originator, Carl Gauss, and represents Gaussian distribution. The Gaussian distribution is symmetrical about the mean and has a bell shape. The height and shape of the bell curve vary according to the standard deviation; the curve is high and narrow for small standard deviations, but low and wide for wide standard deviations.

The central limit theorem is important in relation to the normal distribution. In practice, it means that even if the distribution of the samples being tested is not normal, the sampling distribution of the mean will tend to be normal as long as the sample size is large enough.

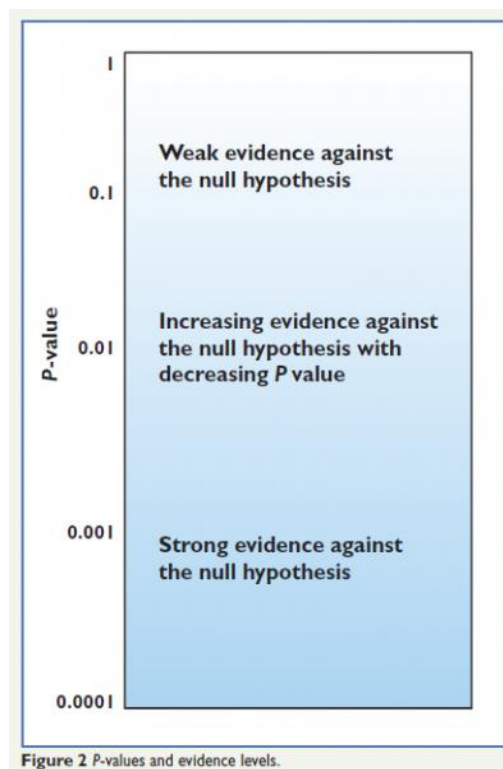
The numbers on the x-axis of the graph (Figure 1) relate to the number of standard deviations away from the mean. Normally, 70% of values are within one standard deviation and 95% within two standard deviations of the mean.



B6. Testing for normality

In order to perform parametric tests (that is, tests based upon the assumption that the data are normally distributed), it is necessary to test for normality. The Kolmogorov-Smirnov test can be used to test for normality. However, a graphical representation using a Q-Q Plot (where Q stands for quartile) is another method of testing whether the data are distributed normally.

B7. P-value and statistical significance



The null hypothesis states that there is no difference between groups, for example an intervention group or a control group, or no association between the variables. The purpose of much medical or dental research is to seek to reject the null hypothesis. Behind this is the reasoning that it is much easier to reject a hypothesis than to prove it; the null hypothesis itself cannot be proven, only rejected or fail to be rejected. A flow chart for hypothesis testing is present at the end of this paper (Supplementary Figure A).

Sample size is important, as an increase in sample size results in a smaller standard error (an inverse relationship), leading to a smaller confidence interval. A test statistic is then used to derive the P-value either from a table, or more often nowadays, by using computer software. Therein lies the reason why the P-value is still often quoted at the 0.05 level, because 0.05 appears in tables that were used to determine it. However, it is better to give the precise P-value from the computer software and then consider the clinical significance of the P-value, even if it greater than 0.05. The term statistically significant is usually applied to P-values when $P < 0.05$, but in reality a P-value of 0.06 may be clinically significant, depending on the circumstances. Figure 2 expresses this concept graphically.

Three common errors in the interpretation of P-values⁴ are:

1. In small, but important studies, if the P-value is greater than 0.05, these studies may not be considered important and further, larger studies, may not be undertaken.
2. All findings when $P < 0.05$ are considered to be a real effect, but in fact on average 1 in 20 instances will be when the null hypothesis is true; that is, no real effect.

3. If the sample size is large, then all statistically significant findings, $P < 0.05$, will be assumed to be important, because extremely small differences will be detected.

C. Displaying data

C1. General considerations

Data may be displayed in a number of ways,³ depending on the type of data (see Table 2). It is very useful to display raw data (that is, unprocessed data) before statistically analysing them because a visual representation of the data helps in the choice of the appropriate method of analysis and identification of any outliers.

Table 2: Data from a radiographic quality study, using the National Radiological Protection Board (NRPB) three-grade quality rating system		
NRPB grading	Number of radiographs	Percentage
1 (excellent, no faults)	55	78
2 (acceptable, but with faults)	11	16
3 (unacceptable)	4	6
Total	70	100

Table 2 and Figures 3 and 4 show different ways of displaying data following a radiographic audit, which is routinely undertaken in dental practice. The data are categorical; that is, the numbers identify the different categories only and have no meaning in themselves. Numbers 1, 2 and 3 correspond to the National Radiological Protection Board's (NRPB) three-grade system for rating the quality of radiographs. The numbers in each category are the frequencies, which may be converted to percentages. If either frequency or percentage is used, the proportions will remain the same; only the labels of the scales will alter.

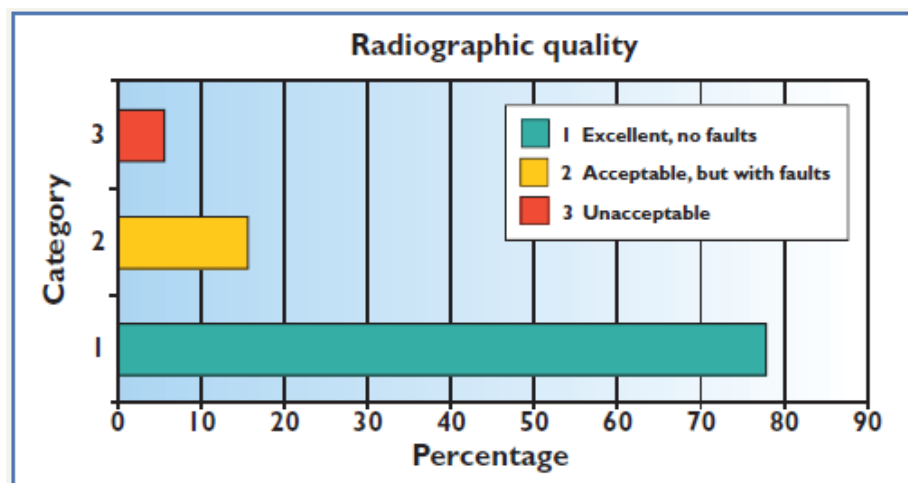
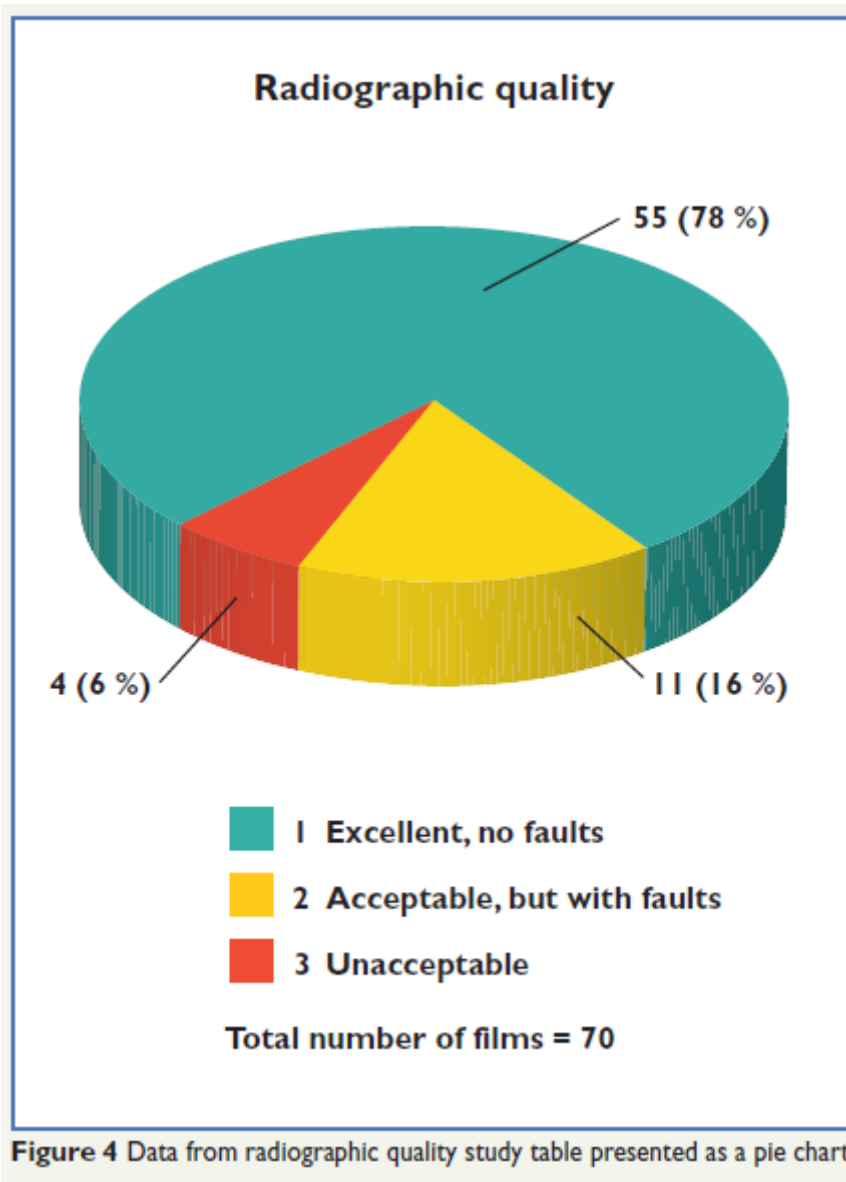


Figure 3 Data from radiographic quality study table presented as a bar chart.



C2. Frequency distribution

Table 3: Raw data from waiting time study: lowest value in blue, highest in red				
Waiting times in minutes				
5	11	3	6	15
3	0	5	1	7
10	9	3	2	0
11	14	7	10	11
0	5	9	8	13
7	7	8	2	14
11	3	4	5	10
7	3	11	14	2
3	10	5	8	1
5	7	0	12	15

When the variables are numerical, the raw data (Table 3) can be presented to show their frequency distribution (Table 4). The data in Tables 3 and 4 are from an audit of waiting times for a single-surgery practice (note that entering a surgery for an appointment before the set time was recorded as zero). A consecutive sample of 50 patients was taken. It is useful to highlight both lowest and highest scores when looking at the raw data, so that the scale range is known. As a practical tip, when transferring data from a paper scoring system to an electronic database, it is useful to use tallying, when four bits of data are struck through, after entry, with a horizontal bar, creating a five-bar gate. It is possible to forget, especially with large amounts of data, which data have been entered and this system assists in creating a clean and accurate data set.

Alternatively, a histogram (Figure 5) could be used to represent these data graphically, after grouping them into time intervals of two minutes each, as shown in Table 4. A histogram displays data by presenting the area of each rectangle as equal to the frequency distribution in that group and the total area of the histogram represents the total amount of data.

Table 4: Frequency distribution of waiting-time data

Waiting time in minutes	Patients (N)	%
0 -	6	12
2 -	9	18
4 -	8	16
6 -	6	12
8 -	5	10
10 -	9	18
12 -	2	4
14 -	5	10
Total	50	100

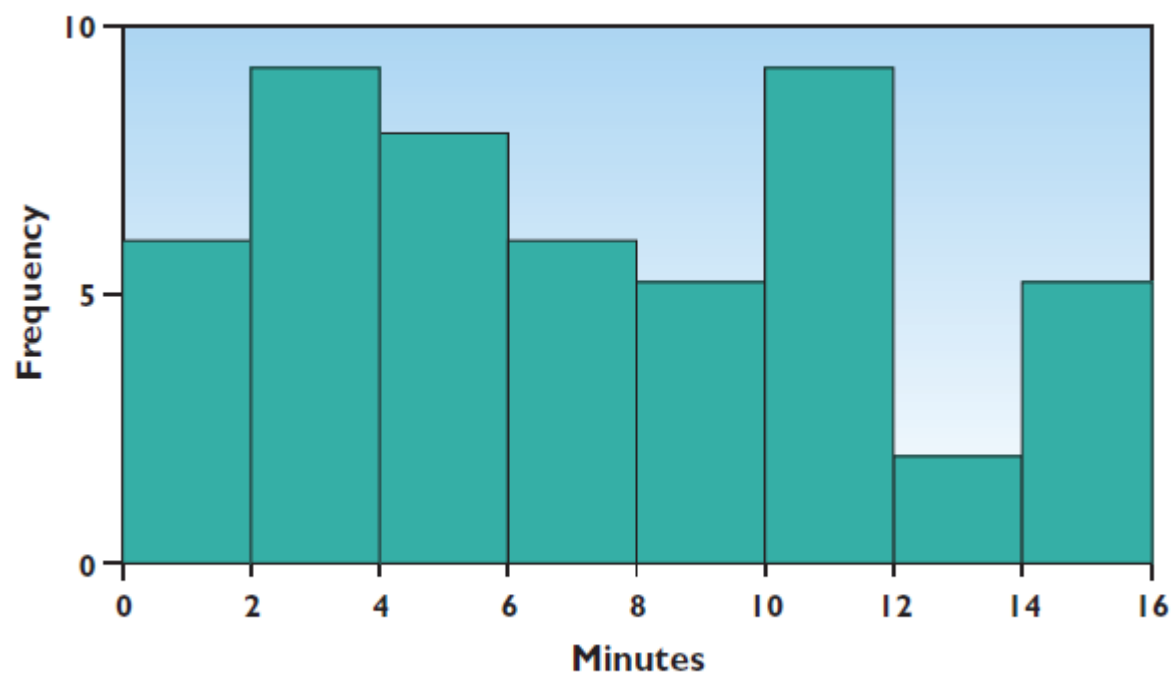


Figure 5 Histogram of waiting times for 50 patients.

D. Some commonly used statistical tests and techniques

D1. t-distribution

Sometimes a distribution similar to the normal distribution is used, but an allowance is made for small sample size when the standard deviation of the population is unknown. This is known as Student's t-distribution. The story behind this rather anonymous name is that William Gosset, who worked for Guinness in the early 1900s, wanted to publish scientific papers, but his employer forbade it, so he used the pen name Student. The t-distribution population curve has wider tails than the normal distribution and less height.

D2. Unpaired t-test and paired t-test

The unpaired t-test is used when using the t-distribution and may be used to test for a difference in means between two groups. When the groups are paired (that is, matched), the paired t-test is used. However, if there is independence between the two groups, the two sample (unpaired) t-test is used.

An example of an unpaired t-test, could be the analysis and comparison of the chronological age of young people with their dental age. Both sets of data must be continuous (that is, from a measurement) and have a t-distribution. When using a one-way analysis of variance, the results will be the same as the unpaired t-test. A paired t-test is used to measure the difference in means between two matched groups and, again, the data must be continuous and have a t-distribution. Paired t-tests are used to find the differences between the data, so that a single sample difference may be calculated. For example, in dentistry, a paired t-test could be used to test the benefit of an oral analgesic versus a placebo for post-operative pain following minor oral surgery. Another example of the use of the paired t-test design could be to compare opposite sides of the maxilla or mandible after different treatments.

D3. Analysis of variance (ANOVA)

Analysis of variance (ANOVA) belongs to the same general linear model shared by linear and multiple regression, except that in the ANOVA model, all the independent variables (independent factors) are nominal. ANOVA is frequently used to compare the means of more than two groups (for two groups, the t-test may be used) and it uses the F-test to test the null hypothesis to determine whether the means of several groups are equal. There are some assumptions that need to be made when using ANOVA. They are that the data have a Gaussian distribution and the variances are similar. If the standard deviations are very different, transformation of the data should be considered (see section D. 13).

A one-way analysis of variance may be used to compare multiple groups of a variable. A two-way analysis of variance has two independent variables and this is why it is named two-way, for example if data are classified by age and gender. Using two-way analysis of variance will reveal whether or not the two independent variables interact with respect to the dependent variable. Two-way analysis of variance is classified as a balanced design with replication, balanced design without replication (an extension of the paired t-test), and as an unbalanced design. It is possible to have a three-way ANOVA, with three independent variables; many studies, for example in dental materials, use this analysis.

A study was conducted⁵ to investigate the interproximal penetration of four different toothbrushes. Because there is only one variable (the type of toothbrush), this known as a one-way ANOVA, but if there had been another variable, for example powered versus manual toothbrushes, then a two-way ANOVA would have been used. Analysis of the data would reveal the P-value for the F-test and whether or not the mean penetration depths of the four different types of toothbrushes are the same.

D4. Regression analysis

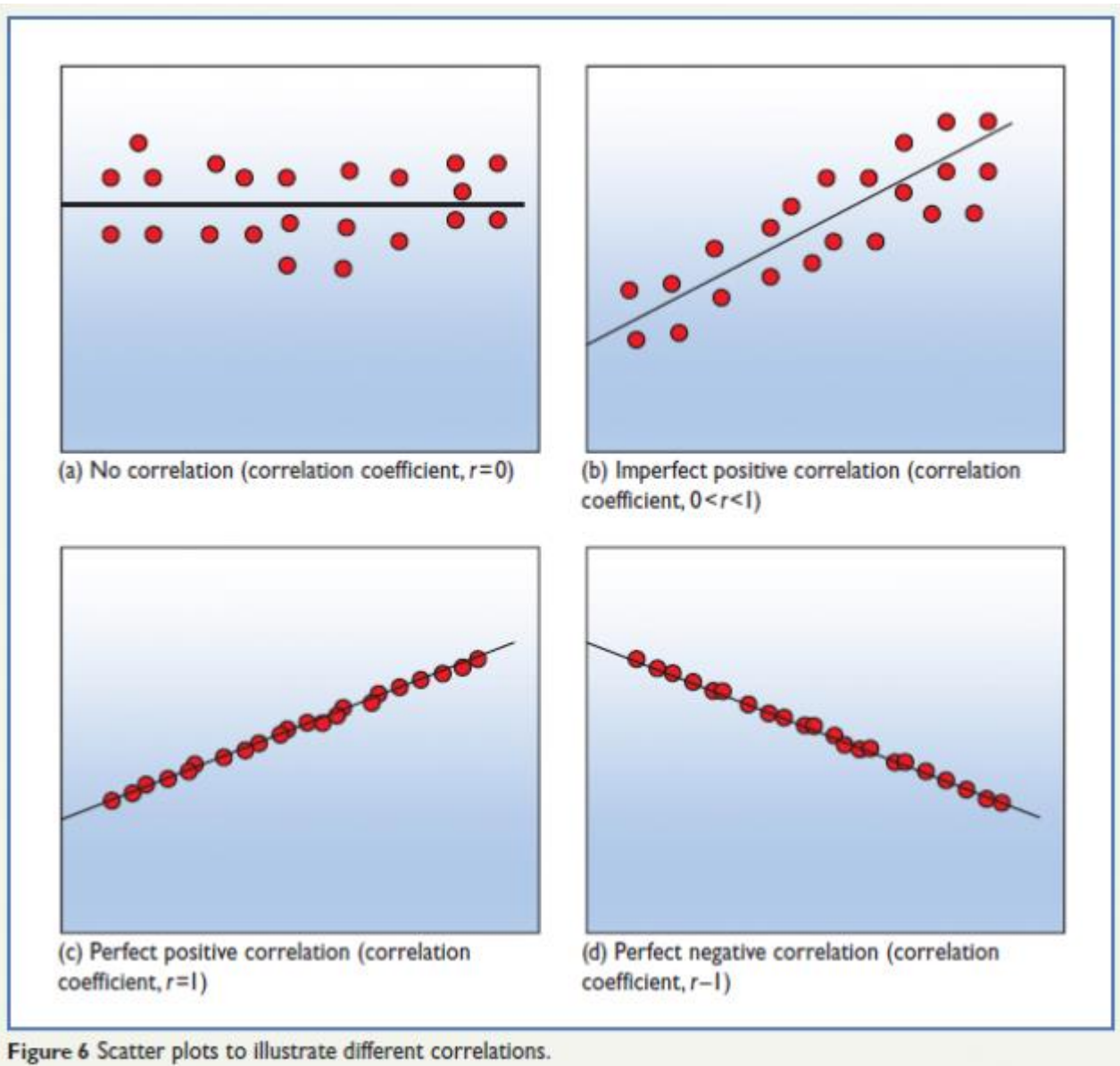
Regression analysis examines the causal relationship between one variable and one or more other variables. Linear regressions are modelled using linear functions; that is, they appear to be a straight line when looked at graphically. The equation for linear regression has a variable or variables (multivariate linear regression model) on one side and the dependent, outcome or response variable (which must be continuous data) on the other side. Problems arise in regression analysis due to confounding variables, when there is an association between the confounding variable, the outcome variable, and one or more other variables. Regression analysis is often complex and accounting for confounding variables is important.

D5. Linear regression

Linear regression is used to establish the relationship between an independent variable and outcome, when both are numerical. In linear regression, only one independent variable is considered, but when there is more than one variable, multiple regression is used to establish the relationship between the independent variables and the outcome. The data are plotted, using a scatter plot and the convention is for the independent variable to be on the x-axis and the outcome on the y-axis. Scatter diagrams are very useful for indicating the strength and direction of an association. Linear regression models generally use the least-squares method to fit the best line between the variable and outcome. An example of linear regression could be that between age and systolic blood pressure, with systolic blood pressure as the outcome and age as the independent variable. When looking at the results following the computation of linear regression, they will be expressed as their estimated coefficient values (β), standard error (SE) and probability value (P).

D6. Correlation coefficient

The correlation coefficient is a number that indicates the strength of a linear association between two variables (although sometimes the relationship may be exponential rather than linear). It is expressed as Pearson's correlation coefficient (r) or Spearman's correlation coefficient(s). The values range from -1 (perfect negative correlation), and +1 (perfect positive correlation) and the further the number is from 0, then the stronger the association. Scatter plots to illustrate these different correlations can be seen in Figure 6.



D7. Multiple regression

It is often necessary to consider more than one independent variable, and for this, multiple regression is used. Multiple regression can identify and allow for the effects of variables that affect the outcome that the study is most interested in finding and can also control for confounding variables. It is important to note that association does not imply causation. A confounding variable (or confounding factor) is when an apparent relationship between a variable masks the true relationship between other variables. The confounding variable correlates either positively or negatively with the dependent and independent variables. An example of a study that would use multiple regression could be a study on the stress factors and stress levels on the dental team. There would be many independent variables involved, for example occupational, demographic and social factors, which could include job demands, support from co-workers, job stressors, job security, pay, working hours, age, pension, and so

on. The term multivariate regression models covers multiple regression and means that more than one independent or exposure variable is related to the outcome variable.

D8. Logistic regression

Although linear regression works with continuous variables, logistic regression is important because in clinical dentistry there are often dichotomous, or binary, outcomes, for example bleeding on probing, when there is either bleeding or not bleeding. Logistic regression provides values for odds, risk and hazards ratios to assess these outcomes.

D9. Parametric and non-parametric tests

A parameter may be defined as a measurable factor or characteristic for statistical use. Parametric tests can only be performed on data that are normally distributed, have equal variance, and are independent: the tests described so far have all been parametric tests. Non-parametric tests are performed on data that are not normally distributed, where SDs are significantly different, and when the parameters of the variable of interest in the population are unknown.

Choosing a parametric or non-parametric test matters the most when samples are small, for reasons summarised in Table 5.

D10. 2 x 2 tables (contingency tables)

It is often necessary to compare dichotomous (binary) outcome variables between treatment groups and the data can be displayed in a table called a 2 x 2 table and then statistically tested using the chi-square test. In the same way that two categorical exposure variables can be cross-tabulated in a contingency table, a 2 x 2 table is used to display data from binary outcomes.

In a 2 x 2 table, the rows correspond to the treatment, or exposure, values and the columns to the outcomes. Table 5 is constructed from fictional data to illustrate a 2 x 2 table, comparing manual versus powered toothbrushing and using bleeding on probing (a binary outcome) as the outcome. The part of the table shaded in blue is the 2 x 2 element, but it is conventional to total both rows and columns.

D11. Chi-square test

Table 6: An example of a 2 x 2 table			
Manual toothbrushing	21	9	30
Powered toothbrushing	6	24	30
Total	27	33	60

The chi-square test is used to see whether there is an association between the row variables and the column variables. It compares the numbers with those that are expected to see whether there are differences between the exposure variables: in Table 6, between manual and powered toothbrushing. For small numbers (total table number under 20) Yates' continuity correction may be used. Table 7 shows the results of the chi-square test and P-value both with and without the Yates' correction factor.

Referring back to Figure 2 (about P-values), the chi-square test in Table 6 provides strong evidence against the null hypothesis, that powered toothbrushes are much more effective than manual toothbrushes at preventing bleeding on probing in this hypothetical instance.

Table 7: Results with and without the Yates correction factor	
Chi-square test without Yates' correction	
Chi-square test result (one degree of freedom)	15.152
P-value	0.0001
Chi-square test with Yates' correction	
Chi-square test result (one degree of freedom)	13.199
P-value	0.0003

D12. Rank order methods

The Wilcoxon rank sum test is another nonparametric test and is used to assess whether an outcome variable differs between two treatment or exposure groups. It is often said to be the counterpart to the (parametric) t-test. To undertake the test, outcome values are put in ascending order; that is, ranked. The Wilcoxon rank sum test looks at the difference between the medians, rather than means of the distributions that have been ranked.

The Mann-Whitney U-test also compares two medians and gives the same results as the Wilcoxon rank sum test, but by a different method. The Kruskal-Wallis one-way analysis of

variance is used when there are three or more groups. The main rank order methods are listed in Table 8.

Table 8: The main rank order methods	
Analysis	Statistical test
Paired samples test (simplified version of Wilcoxon signed rank test)	Sign test
Paired sample difference test	Wilcoxon signed rank test
Two groups difference test	Wilcoxon rank sum test
Two groups difference test	Mann-Whitney U-test (gives the same results as Wilcoxon rank sum test)
Two or more groups difference test	Kruskal-Wallis one-way analysis of variance (extension of Mann-Whitney U-test with three or more groups)
Strength of dependence between two variables	Spearman's rank correlation coefficient
Strength of dependence between two variables	Kendall's rank correlation coefficient (Kendall's <i>tau</i> coefficient)

D13. Transformations

Data collected in dental research are not usually logarithmic, although exceptions to this rule would be when analysing sound level, for example from a dental turbine, when the unit of measurement is a decibel (dB), a base 10 logarithm. However, sometimes it is necessary to transform data using logarithmic transformation and in statistics this is usually to base e , a natural logarithm. Transforming data is done, for example, to make the standard deviations similar, so that a test—for example, the t -test—may be used.

Data may be transformed when there is a substantial skew in the data, so that the data are transformed back to a normal distribution and a confidence interval then calculated: the method used is a power transformation.

E. Analysing qualitative data

Analysing qualitative data is very different from quantitative data because the data are frequently unstructured and come from many sources, for example interviews, questionnaires and observations. Data collection and analysis is often concurrent in qualitative studies⁶ and one of the analytic strategies is to conceptualise the whole of the data and relate it to what is being studied. Software packages are available for qualitative analysis, although their main function to date has been the sorting and storage of information. Some of the software packages available are listed in the next section of this paper.

F. Software packages for statistical analysis

There is a wealth of available software available for statistical analysis. However, much of it is very specialised for certain functions and others have lacked continued development. The software packages in Tables 9 and 10 are those most commonly used for statistics. For many computational activities, even when dedicated software like Minitab or the Statistical Package for the Social Sciences (SPSS) is at hand, it is often more straightforward to use a modern spreadsheet, like Microsoft Excel or Open Office Calc. The latter has the advantage of being free and running on almost every operating system platform, including Apple. For example, in OpenOffice Calc, functions including chi-square test, t-test, median and quartile, standard deviation and Poisson distribution are available. Also, various statistical plug-ins are available for use within MS Excel, from version 97 up until the current product.

Computer-Assisted/Aided Qualitative Data Analysis (CAQDAS) is the use of computer software to aid qualitative research such as transcription analysis, coding and text interpretation, recursive abstraction, content analysis, discourse analysis, grounded theory methodology.

Please note: In the ‘Cost’ columns of Tables 9 and 10, ‘+’ indicates that the software must be purchased, but it is not possible to indicate an exact price as it depends on educational, institutional discounts, and so on. ‘Free’ indicates that the software is either ‘open source’ or freeware. Some open-source software entails more complex installation routines, including the installation of dependent software packages, particularly if it was developed under Linux. The version numbers were correct at the time of writing.

Table 9: Some of the better-known software packages for quantitative analysis

Software	Website	Cost
Minitab (version 16)	www.minitab.com	+
SPSS (version 19)	www-01.ibm.com/software/analytics/spss/	+
STATA (version 12)	www.stata.com	+
Epi Info (version 7)	wwwn.cdc.gov/epiinfo/7/index.htm	Free
MedCalc (version 12)	www.medcalc.org	+

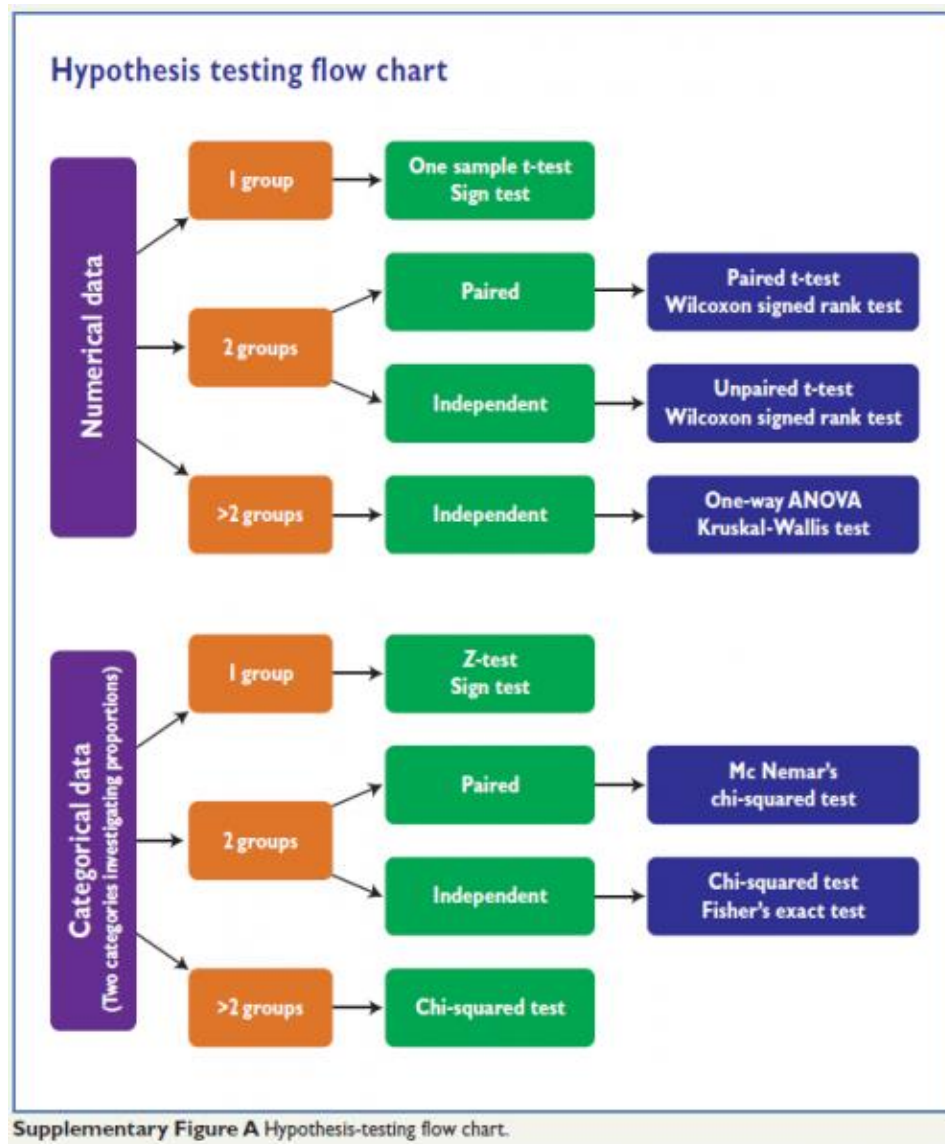
Table 10: Some of the better-known software packages for qualitative analysis

Software	Website	Cost
ATLAS.ti (version 6)	www.atlasti.com	+
Nvivo (formerly NU*DIST) (version 9)	www.qsrinternational.com	+
RQDA (version 0.1-9)	http://rqda.r-forge.r-project.org	Free
Compendium (version 1.5.2)	http://compendium.open.ac.uk	Free

Final thoughts

Analysing the data is clearly a crucial part of any research process and always an exciting one. As stated at the beginning of this paper, ask a statistician first before data collection and preferably before writing the study protocol. In the experience of the authors, statisticians are always very willing to help out with research, whether it is a small or large project, and time spent using the most appropriate statistical tools for data analysis is crucial for the success of the research project.

G. Suggested further reading



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