Understanding Statistics 4

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If the reader of an article can identify the type of data used in a study, this will be instrumental in determining the nature of the statistical analysis. As mentioned in the first article in this series, we have defined three domains of statistics: differences between groups, associations between groups and time-to-event data. This article will focus on statistics associated with the first domain: differences between groups.

I. Categorical Data

We will begin by examining eye colour, a type of categorical data. In a group of 100 boys, let's say 25 of them had blue eyes. If we had a group of 200 girls, assuming the proportions were identical, we would expect 50 of the girls, or 25% of them, to also have blue eyes. Statistics with categorical and its subset of binary data are about dealing with differences in proportions, and the chi-square test is a hypothesis test which provides a P-value, and works by evaluating these differences between groups. In this example, because the proportion 25/100 is equivalent to 50/200, the chi-square value would equal zero, which is the null value. As the difference in this proportion begins to change, the chi-square statistic will increase, and the corresponding P-value will begin to decrease. At some point, these differences may become large enough to reach statistical significance.

Binary data is a subset of categorical data and there are several statistical tests associated with this data type that readers of the literature are likely to encounter. These tests are risk ratios (RR), odds ratios (OR), absolute risk reduction (ARR) and number needed-to-treat (NNT). To understand these principles, one must understand risk and odds.

Example: If four people are ice skating, and one person falls, we would say the risk of falling is simply the number who have experienced the event divided by the total number of people at risk. Thus the risk of the event is 1/4, or 25%, or 0.25. However, the odds of

Table 1			
Exposure	Failure	Survival	Total
Experimental implant	2	8	10
Control implant	6	4	10
Total	8	12	20

Table 2			
Scaling Only pocket depth (mm)	Scaling + Ab pocket depth (mm)	Scaling Only Rank	Scaling + Ab Rank
5.0	4.6	4	1
6.9	4.8	9	3
6.0	5.2	8	6
5.1	5.7	5	7
7.0	4.7	10	2

Table 3			
Participant (scaling group)	Scaling Alone (in mm)	Scaling + Ab (in mm)	Participant (scaling + Ab group)
1	5.0	4.6	6
2	6.9	4.8	7
3	6.0	5.2	8
4	5.1	5.7	9
5	7.0	4.7	10
Mean	6.0	5.0	Mean

the event are calculated as the number experiencing the event divided by the number who have not experienced the event. Thus, the odds would be 1/3, or 0.33. Normally, odds are not expressed as a percentage.

Now let's look at Table 1, often given in a 2x2 table, where we have two groups of patients, one with a control and one with an experimental dental implant. It appears that the experimental dental implant reduces the likelihood of failure, but we would like to quantify this difference.

The risk ratio (RR) is the incidence in the exposed group / incidence in non-exposed.

In this case the RR is incidence in experimental group / incidence in control group.

Thus the $RR = \frac{2/10}{6/10}$ or 0.33.

If both implant types had the same effect, both the RR and OR would take a value of 1, which is the null value.

If the $RR < 1$, experimental implant appears to decrease the failure rate

If the $RR > 1$, experimental implant appears to increase the failure rate

Be careful if the outcome is survival, in which a beneficial result from the experimental implant would have a $RR > 1$ and an adverse effect would have a $RR < 1$.

As the RR is 0.33 we would say that the risk of failure with the experimental implant

is 1/3 of what it is with the control implant, or that the risk of failure is reduced by 67%.

The odds ratio (OR) is the odds in the exposed / odds in the non-exposed. Therefore the OR is $\frac{2}{8}$ $\frac{6}{4}$ or 0.17.

This means the odds of failure are 17% of what they are with control implant, or the odds of failure are reduced by 83% with the experimental implant.

ORs tend to exaggerate treatment effects, as the OR is always further away from the

null value as compared with the RR (0.33 vs 0.17).

We can also calculate the ARR and NNT from this data set.

The ARR is simply the risk difference: 60% - 20% = 40% meaning the risk of failure with the experimental implant is reduced by 40%.

The NNT is the reciprocal of the ARR (not expressed as a percentage) or $1/0.40 = 2.5$ (rounded to 3). This means we would have to treat 3 patients for the next patient to benefit from the experimental implant. NNTs are a way for practitioners to estimate the

clinical benefit of an intervention. The null value for the ARR is 0, and the null value for the NNT is infinity, meaning if the groups are identical, then an infinite number of patients would need to be treated to see any clinical benefit.

II. Ordinal Data

Before we discuss ordinal data statistics, a brief introduction to normal and skewed distributions is needed. If we took a large random sample of adult males living in London and wanted to know their height, it is likely this will follow a normal, or Gaussian distribution (Fig 1). With a normal distribution the mean (numerical average), median (middle value) and mode (most common value) are the same. Thus, the greatest number of men would be at the average height, with fewer men as we deviate from this average. Sometimes, data do not follow a normal distribution and can be skewed to the left or right as in Figure 2. Data such as the number of pregnancies are typically right-skewed, as there will be many women with either 0, 1, 2, or 3 pregnancies but few with 4, 5, 6, etc.

If our data set is 1,2,2,3,3,3,3,4,4,5, this would be normally distributed with a mean, median, and mode taking a value of 3. But changing just one value, say changing the "5" to "50" would make these data right-skewed. In this example, the mean is no longer 3, but the median value stays the same. In general, the median is much less sensitive to extreme values than is the mean.

Figure 1. The Normal (Gaussian) Distribution

Figure 2. Positively and Negatively skewed Distributions

Table 4			
	categorical	ordinal	quantitative
description	different categories of data; none better than the other	different categories with one level better than the other, yet imprecise	real numbers with precise meaning; pocket depth of 4mm twice that of 2mm
examples	eye colour, hair colour, city of origin	mild, moderate, or severe periodontitis; Likert scale	age, height, alveolar bone level (mm)
common statistical test	chi-square	Mann-Whitney U	t-test
how test works	differences in proportions	differences in rank order	differences in means
null value	$X^2 = 0$	median difference = 0	mean difference = 0
	binary data		
description	only 2 categories		
examples	male/female disease/no disease		
common statistical test	RR null value = 1 OR null value = 1		
common statistical test	ARR null value = 0 NNT null value = ∞		

At this point we will introduce the terms parametric and non-parametric tests. Parametric refers to parameters of, in this case, the normal distribution, and parametric tests assume the data are normally distributed. Non-parametric tests make no such assumption on the distribution of the data, and generally look at differences in medians rather than means.

Let's look at a hypothetical parallel-group randomized trial of 10 patients comparing deep scaling alone to deep scaling and antibiotic gel. Our periodontal outcomes could be stages of periodontitis, expressed as none, mild, moderate or severe, which would be

ordinal data. However, we will express the outcome as periodontal pocket depth (quantitative data) for illustrative purposes. We are using a non-parametric test as the data are not normally distributed, often the case with small samples.

It appears that the scaling plus antibiotic gel group has done better than the control group. Statistical tests for skewed quantitative data, such as the Mann-Whitney U test, use the *rank order* of data values, rather than any values themselves. For example, if we had the following data sets for two groups of patients with different degrees of periodontitis, we would rank them in order of severity

without using the actual data values. Because we are using rank rather than actual values, non-parametric tests such as the Mann-Whitney U test are not as precise, and thus, we need *larger* differences between groups to reach statistical significance.

III. Quantitative Data

Quantitative data represents numbers with precise mathematical meaning and statistical tests for this data type deal with *differences in means*. The most common hypothesis test for quantitative data is the t-test, which works by examining these differences. Let's examine our same randomized trial measuring differences in periodontal pocket depth. If the mean pocket depth in the control group was 6.0mm and the mean depth in the test group was 5.0mm, the mean difference would be $6.0 - 5.0 = 1\text{mm}$ (Table 3). Because we are dealing with actual numerical values, it is easier to achieve statistical significance with parametric tests such as the t-test compared with the non-parametric Mann-Whitney U. This is relevant as investigators occasionally use parametric tests with ordinal or skewed quantitative data.

Summary

Statistical tests for categorical, ordinal and quantitative data deal with differences in proportions, rank order and means, respectively (Table 4). In the next paper, we will give hypothetical passages from dental studies using different data types, asking and answering a series of questions from these passages.

Evidence-Based Dentistry (2011) 12, 25-27.
doi:10.1038/sj.ebd.6400781.