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Qualitative and quantitative analysis

Data, information, knowledge and wisdom

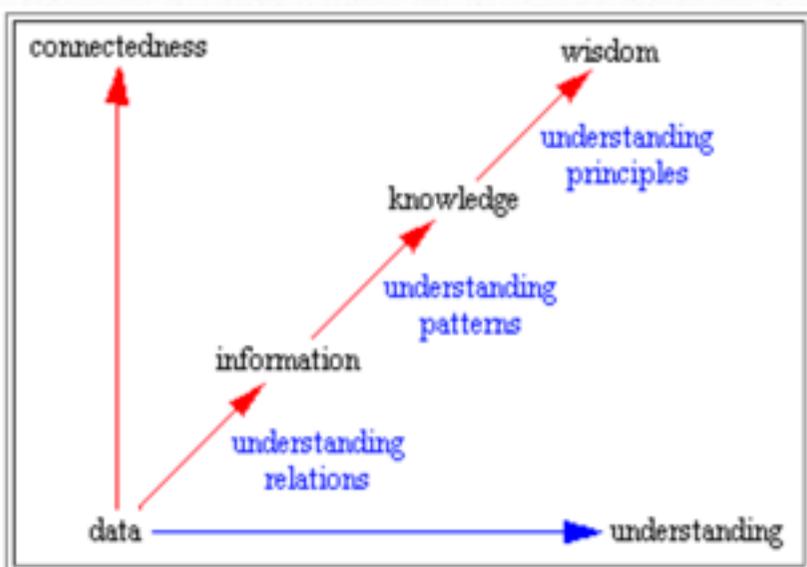


Diagram from <http://www.systems-thinking.org/dikw/dikw.htm>

Unprocessed (raw) data is not, of itself, information or knowledge. Ackoff (1989) describes how data only becomes information through an analysis of the underlying relationships within it. Ackoff then develops this idea further by suggesting that a **recognition of patterns within this information**, linking it to known situations, principles, contexts (or 'real-life') converts information into **usable knowledge**. Finally, a critical evaluation of this knowledge further

enables us to identify any deeper principles that can be generalised to a wider context and to make predictions about future outcomes

(**wisdom**).

Ackoff's model, could just be considered to be an interesting philosophical model of 'knowledge development'. The model does however have a useful relevance in understanding the process of structuring and writing a research project (see right).

For more information on the relationship between data and higher knowledge, see [BBC GCSE Bitesize](#).

Data	Information	Knowledge	Wisdom
Place 'raw data' in Appendices	Include processed data (tables, charts and summaries, etc) in Results	Interpret the information in relation to your research topic in Results	Critically evaluate your results to identify 'deeper' principles and implications in Conclusions

Types of data

Data comes in various forms but is often described as belonging to one of two types. Quantitative data is typified by having numerical characteristics, whereas Qualitative data is more 'language-based' and is typically described in terms of categories, key themes and descriptive features.

Type	Examples/Forms	Typical Sources
Quantitative:	measures, totals, scores	tests/exams counting responses or incidences scaled answers to questions
Qualitative:	opinions, views, explanations, discussion summaries	surveys interviews focus groups

Converting data into (meaningful) information

It is difficult to make judgements about the meaning of unprocessed (raw) data. Further, any judgements regarding individual bits of data, in isolation, may be misleading or unreliable.

For example, is a test result of 74%, a good score? Well, that depends on how everyone else performed in the test..... if the average test result was 86% and results varied from 72% to 94%, then a seemingly good score of 74% would be nearly 'bottom of the class'.

Similarly, a particular opinion that keeps on surfacing over and over again in interviews will be clearly more significant than one that only arises once or twice. What this tells us is that we must look at the whole body of data before it can yield up useful and reliable information.

The first stage of data analysis is therefore to find relationships within the entire body of data, and this is the process by which data can become 'information'. The way we find relationships in a set of data depends on whether it is qualitative or quantitative.

Type	Key Relationships	Method
Qualitative:	Are there key themes or categories of responses?	e.g. Affinity Diagram
Quantitative:	Where does the bulk of the data lie? (Central Tendency) How variable is the data? (Variance/Variability)	measures of average measures of range

Key relationships in qualitative data can be found by analysing responses for obvious themes (affinities). For example, consider responses to the following question:

What did you hope to gain from attending this course?

“a job”

“I just wanted to know more about this”

“better prospects”

“I would like to go to university”

“I really like coming to the college”

“I expected to be able to understand the subject better and be able to explain it to others”

“better pay at work”

“I would like to do my own research around this”

“I enjoy working with people who are into the same things as me”

The expectations of students in this study would seem to cluster around some key themes and is therefore possible to group responses that share the following ‘affinities’:

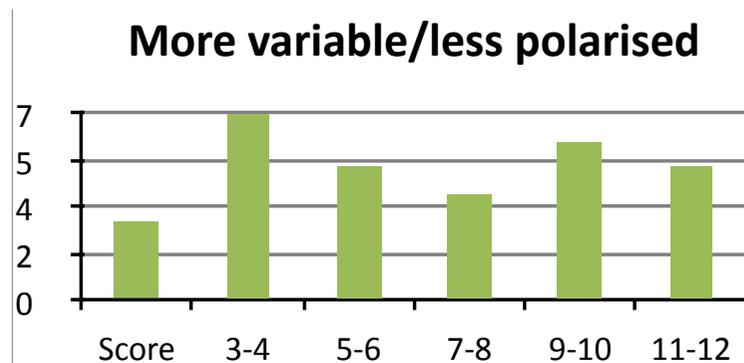
- career development
- knowledge for knowledge’s sake
- progression opportunities
- social aspects of being a student
- anything other*

* Most qualitative data can be grouped around 5 or 6 categories including one for ‘any others’ that are less frequently occurring and more diverse.

Sometimes, coding into simple categories such as “positive”, “negative” or “neutral” may be all that is required.

Key relationships in quantitative data: (as mentioned above) are typically defined by:

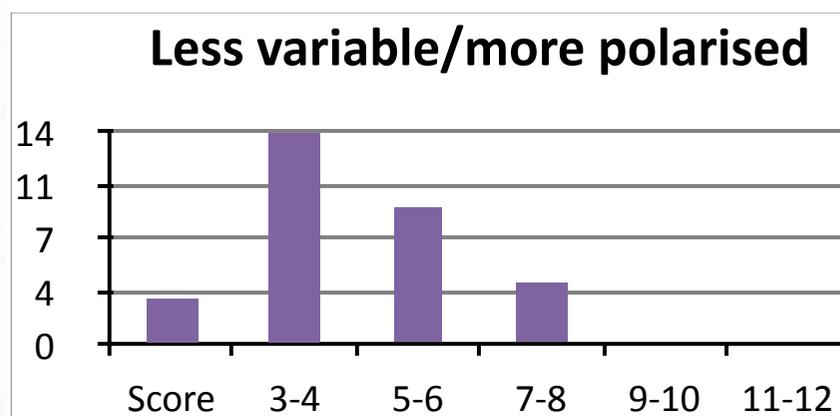
1. the average of the data (giving a sense of where the data tends to cluster);
2. the range of the data from the smallest to the largest, recorded values (giving a sense of how polarised - or tightly clustered – the data points are around the average value.



This chart (left) depicts data that is quite variable (data ranging from 1 to 12) and without a clear sense of average* (there are more results scoring '3-4', but this is only one more than those scoring '9-10' and two more than those scoring '5-6' or '11-12').

* Measures of average are discussed more below.

The chart to the right shows data that appears far more polarised or clustered around the bulk of the data between '3-4' and '5-6'. The range of the data is compressed to varying between 1 and 8.



This sort of analysis helps to 'distil' information out of the data. In this case, the first (green) chart suggests that there is significant variation in these scores and no real sense of a meaningful average score. The second (mauve) chart, however, seems to illustrate a set of scores that are more similar with a stronger sense of an average score.

Note: charts like these can be produced relatively easily using Chart Wizard in Microsoft Excel and then copied into a Word document. [How to use Chart Wizard in Microsoft Excel](#)

Generating knowledge out of information

Changing this information into knowledge would require us to translate this 'disembodied' information into the context of our research project. For example:

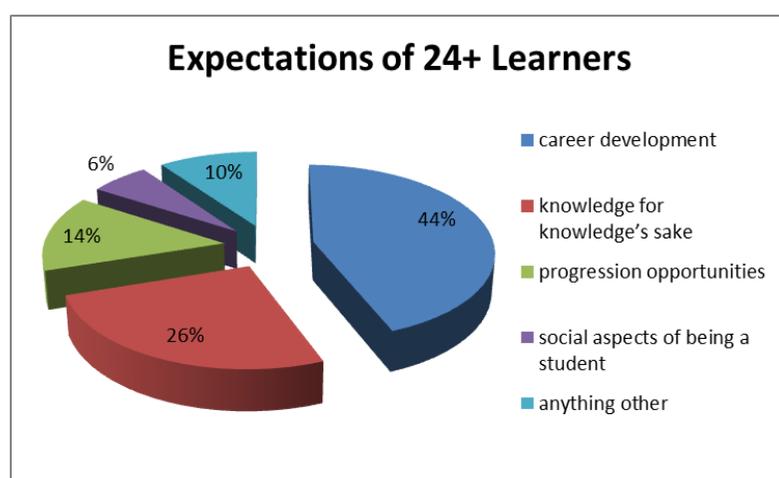
“the ‘green’ chart suggests maths ability in this group of learners are very variable, creating significant challenges for both delivering highly differentiated learning activities and for facilitating more consistent levels of achievement.”

“the ‘mauve’ chart suggests that maths ability in this group of learners is fairly consistently skewed towards lower levels of prior achievement and that there is a pronounced need for support across the entire cohort.”

Qualitative information is, in many ways, easier to interpret and express as knowledge because the data and resulting information is already expressed in language rather than in abstract mathematical terms. For example (and referring back to our earlier example):

“the majority of responses from the 24+ employed learners related to ‘career progression’ (44%) with 26% of responses, relating to ‘knowledge for knowledge’s sake’, being the second highest. In contrast, the 16-19 group of learners more frequently identified ‘social aspects of student life’ as being a major expectation (41%) with other reasons about equally cited (between 11 and 16%).”

Quantising qualitative data



The example above illustrates how grouping or categorising qualitative data can then be ‘quantised’ by simply counting the number of responses that fit within each category. The results of this analysis can then be displayed as bar-charts showing the number (frequency) of responses in each category. An alternative and perfectly acceptable approach would be to

convert simple counts of responses (within a category) into percentages which can then be displayed effectively as a pie-chart.

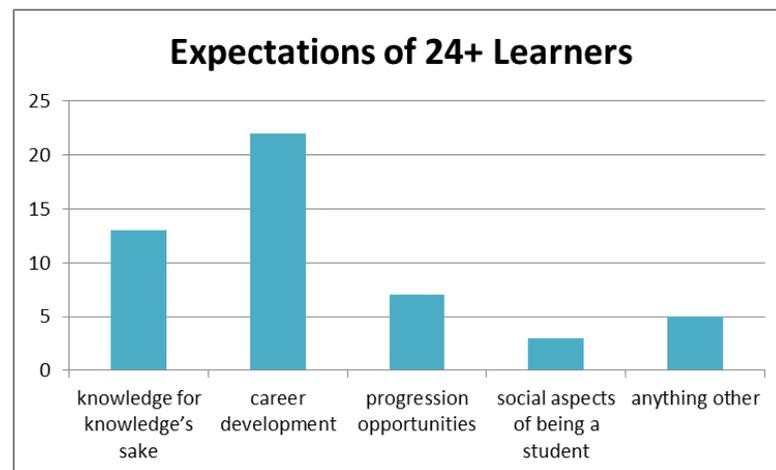
Different measures of average

When we use the term ‘average’ in general speech, we tend to think about the formula that we most likely learnt at school - this is correctly known as the Arithmetic Mean (or just ‘Mean’).

$$\text{Average} = \frac{\text{Total (of a set of scores)}}{n \text{ (number of scores in the set)}}$$

Learner	Pocket Money
1	£8.00
2	£7.50
3	£10.00
4	£12.50
5	£12.00
6	£120.00
7	£5.00
8	£0.00
9	£10.00
10	£15.00
Total	£200.00
Mean	£20.00

There are two circumstances when this measure of average is either not feasible or inappropriate. The first circumstance is where you have collected and grouped **qualitative** data and your analysis has produced simple counts (or ‘frequencies’) of responses within a series of categories. Consider, for example, the chart to the right. It would not be possible or meaningful to calculate an arithmetic mean of this data because you would have to add together qualitatively different sub-sets of data. (If we have 10 apples and 5 pears, would it be meaningful to say we have an



average of 7.5 apple/pears?). In this situation, you would use a measure of average known as the Mode, which is simply the most frequently occurring category within the set of data. In this case, the mode is ‘career development’ which received 22 responses.

The second circumstance is where your **quantitative** data includes some occurrences of unreliably extreme data. Imagine you survey 20 learners to find out how much pocket money they receive, at home, with the results as depicted in the table to the left. You may notice from this data (raw results) table that 9 out of the 10 learner’s pocket money is less than £15 and most of it being below £12.50 – yet the arithmetic mean is £20. In this situation the mean is not a reliable indicator of the average amount received by these 10 learners and this is because Learner 6 has particularly wealthy parents and a weekly pocket money allowance of £120. These is clearly a relatively extreme value for the general demographic of learners in the group and such extreme values tend to make the arithmetic mean unreliable as a measure of average.

Order	Learner	Pocket Money
1st	8	£0.00
2nd	7	£5.00
3rd	2	£7.50
4th	1	£8.00
5th	3	£10.00
6th	9	£10.00
7th	5	£12.00
8th	4	£12.50
9th	10	£15.00
10th	6	£120.00
	Total	£200.00
	Mean	£20.00

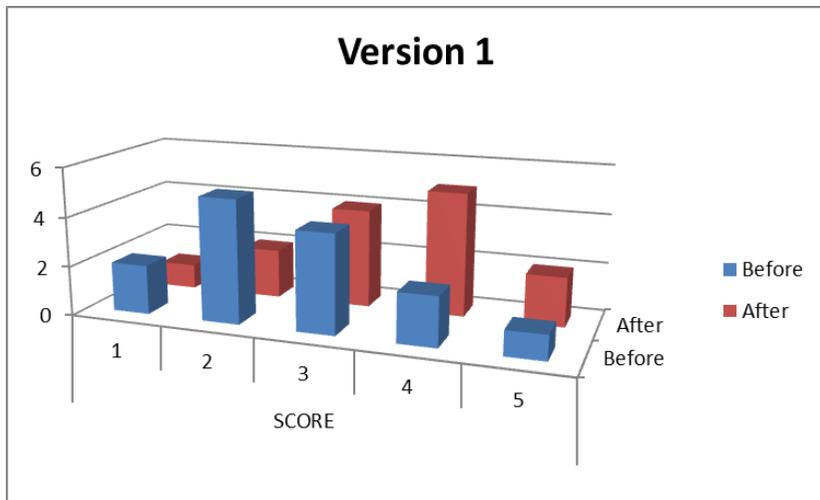
In such circumstances as the above, a more reliable measure of average would be the Median value. This is obtained by rearranging the data into numerical order and then identifying the value at the mid-point (see right). In this case the mid-point value can be found between the 5th and 6th value when arranged in order. This is £10 and is clearly a more reliable measure of average for 9, out of 10, of these learners.

A summary of some common ways of describing quantitative data is shown below.

Descriptive Statistics	(Arithmetic) Mean – commonly known as the average = sum of values/number of values
	Median – the middle value when all the values are arranged in order from lowest to highest
	Mode – the most frequently occurring value (most appropriate when measuring the number of occurrences within a category e.g. eye colour)
	Range = difference between the highest and smallest values
	Interquartile Range – (a) arrange all the values in order from the lowest to the highest; (b) work out the values that lie at the $\frac{1}{4}$ and $\frac{3}{4}$ positions along the series (similar process to calculating the median, which is the value at the $\frac{1}{2}$ way point) – these are the 1 between these two values – its purpose is to avoid extreme values giving a false impression of the spread of the data.
	Note 1: measures of average (mean, median and mode) tell you where the bulk of the data lies - (if the average height of men is 5'7", then most men are somewhere around this height). Note 2: measures of variance (range and interquartile range) tell you how far the data spreads around this average.

Drawing conclusions (from knowledge to wisdom)

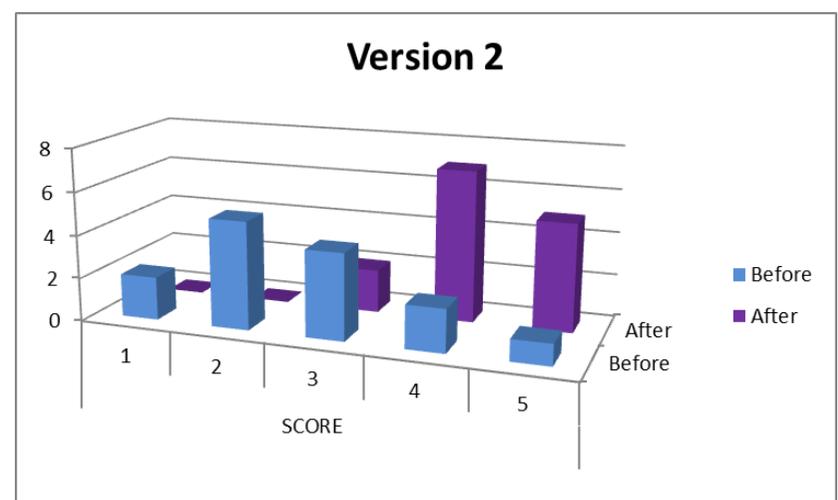
You will need to draw conclusions from the knowledge you have gained from carrying out your project. This requires a thorough, critical evaluation of what your analysis of results truly indicate and whether these conclusions can be used as a reliable evidence-base for future action (e.g. to further 'roll-out' your intervention or to initiate further research). A central judgement to be made here will be to consider 'can we be sure that there has been a real change/ improvement?'



Consider the ‘before and after’ results shown as two parallel bar-charts, to the left. It is clear that there has been a shift in the modal average from ‘2’ to ‘4’, but the range (variability) of the data is fairly ‘wide’ in both cases. Is this evidence of improvement or simply natural or random variation that occurs when measuring things which are subject to ‘human factors’?

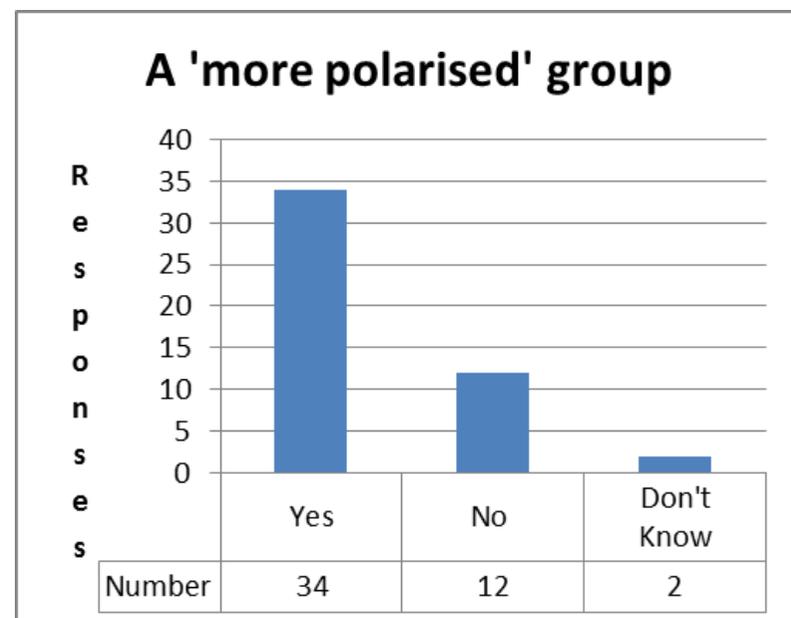
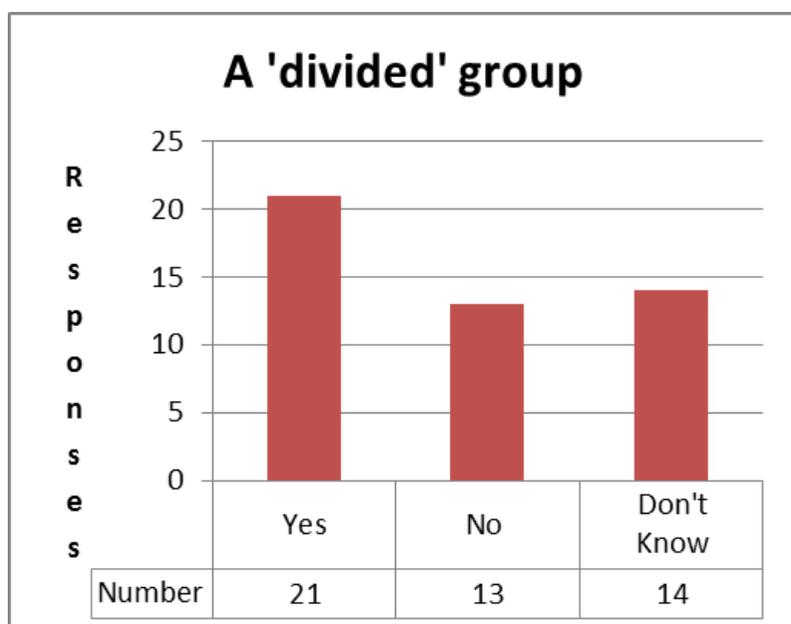
Whilst the apparent change/improvement in the average score in Version 1 is encouraging, the variability in the data makes it difficult to be fully confident that this is a real effect of your project intervention rather than just a random fluctuation.

Now consider Version 2 showing a different spread (or distribution) of data in the ‘After’ situation. Here, the mauve bars show a similar shift in modal average from ‘2’ to ‘4’, but this time the variability of data has been reduced and scores are more polarised around this ‘new’ average. This should increase our confidence in Version 2 as evidence of real (significant) change.



Being confident about the meaning of data

Developing a ‘feel’ for the significance of data - and for changes in data – is a very valuable critical thinking skill. In ‘pure research’ this is taken much further and researchers would be expected to carry out ‘statistical tests of significance’ to calculate the probability of data representing ‘real effects’ of changes made as part of the experiment. This would not be practical, and is not expected in Practitioner-Led Action Research which, after all, has to be an easily managed process if it is to be a readily used and effective means of driving quality improvement. However, the ability to evaluate data at an informed, but intuitive, level is – as mentioned above – a very useful skill for all professionals and teachers, in particular.



We have looked at the use of measures of average and variability in trying to understand quantitative data. Here is another example to consider, above. The chart on the left suggests a preference for 'yes' but 'no' responses are also quite high, with even more 'undecided'. If this were the result of asking 48 learners, "have you improved your skills in maths as a result of this lesson?", what might you conclude from the chart on the left? Would you be more confident if your results looked like the chart on the right – and if so how would you justify this in your 'conclusion section'?

Finally, and to help you in making *wise* judgements about the outcomes of your research, here are some other questions you should ask yourself when evaluating data and making judgements about it (drawing wisdom out of knowledge). These questions will 'sharpen your critical senses' whenever you need to evaluate statistical findings.

1. How large was the sample in the study? In the Version 2 chart, above, would you be more confident in the outcome of the research if the numbers in the vertical axis were in hundreds (e.g. 8=800 learners, not just 8)?
2. Might other things be causing the observed changes in the data? Might learners' scores have increased because you did something different with them (they were less bored and more engaged) rather than specifically what you did that was different (e.g. trying a specific approach to improving learners' English skills)?
3. What further research might be necessary to increase your confidence in the results or to clarify potential causal factors?