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Quantitative versus Qualitative Approaches to Tacit Knowledge Testing

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ABSTRACT

Research in knowledge management covering tacit knowledge tends to be descriptive and often makes little use of empiricism. Psychology as another discipline is very empirical and tends to use statistics to process quantitative data. There are alternative approaches to interpreting data that do not rely on reductionist approaches along numerical lines. We do not negate statistics; rather we provide an alternative to statistical processing of empirical tacit knowledge data. Using empirical data, we show how graphical, qualitative data analysis was used to interpret lower level patterns in the data on tacit knowledge enabling more meaningful quantitative data analysis

INTRODUCTION

Tacit knowledge is a form of knowledge that is typically not written or taught directly. It is possible to split this knowledge into two types being that of articulable and inarticulable tacit knowledge. The former are the street smarts, shop skills or trade secrets, which can be passed on. Strictly speaking this is not really tacit knowledge. The latter is a truly tacit form of knowledge that requires deeply embedded personal use of sense and meaning for us as individuals to understand and make use of the knowledge. In this paper we limit ourselves to talking about the former type. What is presented here is not simply a presentation of tacit knowledge, but rather a discussion of the means of testing and more importantly analysing such knowledge. The work offered here is based on sample data acquired by questionnaire through three Information Technology (IT) firms.

The goal of the paper is to show an alternative to the use of descriptive statistics for data analysis. In our study we had small sample sizes that were not appropriate for the kind of quantitative analysis needing large sample sizes. We have thus used a qualitative and graphical approach to analyse the data, known as formal concept analysis (FCA) (Ganter and Wille 1999). Specifically we were interested in identifying individuals who responded similarly to peer-identified experts so that the organisation would be alerted to the potential value of these "quiet achievers".

THE TACIT KNOWLEDGE INVENTORY

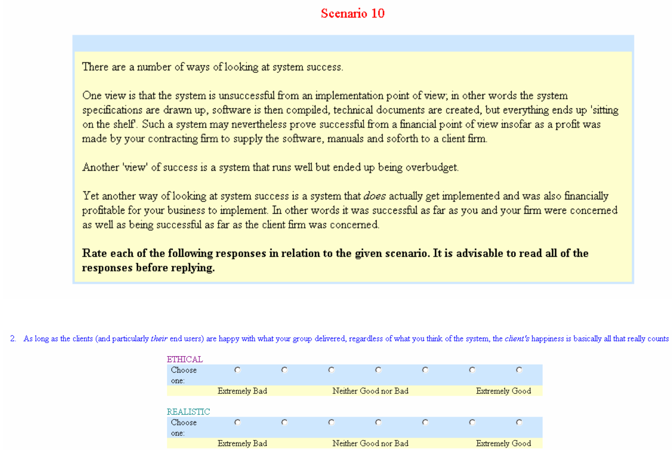
There have been a number of approaches to measuring tacit knowledge. The most validated approach is the use of workplace scenarios and answer options along the lines of a Sternberg *et al.* (2001) psychological testing instrument. While most of the work of Sternberg and his associates has been in the psychology and management areas, we were interested in the IT domain. Our work, thus, is applying and testing the approach to a new domain and has resulted in the development of an IT tacit knowledge inventory. Another differentiating feature is that we do not have: a) random respondents, b) large sample populations or c) captive participants. Thus for data modelling we chose to use Formal Concept Analysis with its lattice-based means of representing data. In addition to measuring tacit knowledge, we mapped knowledge flows between the individuals using social network analysis (SNA) (Scott 1991), though this is not discussed in this paper.

In order to obtain a sample data set, empirical research was conducted in three IT organisations. In each organisation, we measured the extent to which a person could be said to possess tacit knowledge using our own inventory of IT workplace scenarios and answer options along the lines of an instrument. We stress the makeup of the organisations are not the central theme here, rather the possibilities for data processing of tacit knowledge, beyond the use of just statistics. For readers interested in further details of the case studies, our research goals, methodology and findings are provided in Busch and Richards (2003). Very *briefly*, the tacit knowledge inventory was composed of 16 IT workplace scenarios with relevant answer options for each given scenario. In total there were 126 answer items for all 16 scenarios together. The number of answer items varied from as few as 6 answers (Scenarios 5, 9, 13) up to 12 answers (Scenario 3). Figure 1 shows the text for scenario 10 with answer option 2. Respondents used a 7-point Likert scale to select an ethical (*what should you)* and a realistic (*what would you do)* answer for each answer option, for each randomly assigned scenario. Behind each of the Likert Scales were numerical values, where Extremely Bad was represented with a numerical value of 1, through to Extremely Good with a value of 7. In addition to this, respondents were asked to identify peers they felt were 'proficient' in their work related tasks. The proficient personnel became the 'expert' sample whose results would be compared to the results of others.

QUANTITATIVE DATA ANALYSIS

As Likert scale data is ordinal, descriptive statistics were able to provide an indication of: (1) whether experts in general were answering the tacit

Figure 1: Illustrating sample scenario 10, answer option 2 and 7-point Likert scale used in the online tacit knowledge inventory.



knowledge inventories differently from novices; (2) which particular scenarios and answer options were being answered differently by experts; (3) which scenarios and answer options showing the greatest degree of variation between how experts differed in terms of their ethical and realistic answers as compared to novices; and (4) which individuals who were not actually identified by their peers as being experts, ended up having answers (ethically and realistically) close to that of experts. The descriptive statistics produced for all questionnaire results included: Mean, Median, Standard Deviation, Minimum and Maximum values (1 to 7 in the case of the Likert scale), Count (of the number of respondents who had answered the scenario/answer combination) and Confidence Level (95%). This process was repeated for each Organisation's data. Tables 1a and 1b show the results for scenario 10, answer option 2.

The descriptive statistics shown in table(s) 1 illustrate several things. Firstly the control (or novice) group's statistics are provided on the left hand side, with the expert's statistics are on the right. Starting with the count given towards the bottom of each table, we see that 15 novices answered this question dealing with this scenario, whereas 9 experts did so. These figures represent those from one of the three organizations who answered this section of the inventory. We see that the Means were 5.7 (ethical) and 5.2 (realistic) for novices, but 3.7 (ethical) and 4.6 (realistic) for the experts. In other words the experts were inclined to be more negative ethically and more noncommittal realistically when dealing with this answer, than the novices who considered the option to be good on the whole. Examining the median values we also note that the experts tended to be negative (3.0 or Bad) ethically but positive (5.0 or Good) realistically. The novices did not vary so much in their ethical or realistic responses which were 6.0 (Very Good) and 5.0 (Good), respectively. This sample shows a clear difference between the two groups. This is not the case for all scenarios and answer options. Also, the trends in this scenario could have been completely different for alternative options and scenario combinations. In general, the experts were more reserved in their responses. More substantial statistical testing took place in the form of a Wilcoxon test.

THE WILCOXON MATCHED PAIRS SIGNED RANK TEST

The statistics that had been completed up until now were simplistic and descriptive, and furthermore were conducted on small a small sample size. The Wilcoxon nonparametric statistical test (Siegel 1956) permits a one tailed test of statistical significance on data to determine whether in fact *statistically*, experts and novices were answering the scenario questions in different ways. At the same time the intention of this research was also to identify other individuals who attained results similar to that of experts but were not necessarily recognised by their peers as such. This group we label '*expert non-experts*'. Alternatively the term acronym ENE will be utilised from time to time. For the readers information we may like to think of these expert non-experts as expert-novices. That is to say people not formally identified by their peers as experts, nevertheless their test results indicate they were similar in their answers to that of experts.

With regard to undertaking a test between experts (as the respondents were so identified as part of the questionnaire process) and novices, the following results were achieved (using the medians). A number of tests were conducted. First for all the organisational data combined (as this was recommended by the Statistics Department at our University, given that the tacit knowledge inventory was the same for all three IT organisations, and that combining the results would increase the sample size). Second a test just for the largest of our organisations (Organisation X), which of any of the organisations would have had the largest statistically significant data set. And third (and the main purpose of the test), to see if there was any difference between the scores of experts and novices. We see the results of this in table 1c. Note that were unable to find a statistically significant difference, insofar as the null hypothesis has been rejected. We will reconsider these results again later.

Table 1: A sample of descriptive statistics from Scenario 10, answer 2 (Tables 1a and 1b) and Wilcoxon test results where the expert sample has been compared with the control population

Scenario 10 - 2nd Question	Ethical	Realistic
Mean	**5.7**	**5.2**
Standard Error	0.3	0.3
Median	**6.0**	**5.0**
Standard Deviation	1.2	1.3
Minimum	3.0	2.0
Maximum	7.0	7.0
Count	**15.0**	**15.0**
Largest(7)	6.0	6.0
Smallest(1)	3.0	2.0
Confidence Level (95.0%)	0.7	0.7

Table 1a: Novices

Scenario 10 - 2nd Question	Ethical	Realistic
Mean	**3.7**	**4.6**
Standard Error	0.7	0.7
Median	**3.0**	**5.0**
Standard Deviation	2.2	2.1
Minimum	1.0	1.0
Maximum	7.0	7.0
Count	**9.0**	**9.0**
Largest(7)	2.0	3.0
Smallest(1)	1.0	1.0
Confidence Level (95.0%)	1.7	1.6

Table 1b:Experts

All three organisations combined.
Null hypothesis: declares there is no difference in the scores (Likert scale 1-7) between *experts* and *novices*.
Statistical significance: $z = -1.1$
Answer: We cannot reject the null hypothesis
Just organisation X (the largest of our organisations)
Null hypothesis: declares there is no difference in the scores (Likert scale 1-7) between experts and others.
Statistical significance: $z = 1.4$.
Answer: We cannot reject the null hypothesis.

1c: Wilcoxon text results

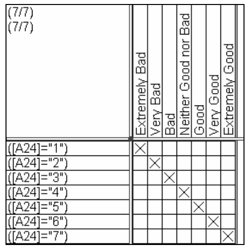
THE USE OF FORMAL CONCEPT ANALYSIS

The adoption of Formal Concept Analysis has occurred for a number of key reasons. First of all there was a desire to model the tacit knowledge inventory results (elicited by way of a questionnaire) in a visual environment, which would permit finer interpretive granularity. Second it was expected that the sample sizes would be too small to permit effective quantitative interpretation of the datasets along traditional Sternberg/psychology lines. Third the graphical Formal Concept Analysis (lattice theory) based approach has allowed us to uncover a group of individuals who behaved similarly to their peer-identified experts thus becoming known in this research as 'expert non-experts' (previously mentioned). Through a worked example, let us now examine this alternative or rather complementary means of interpreting the questionnaire data.

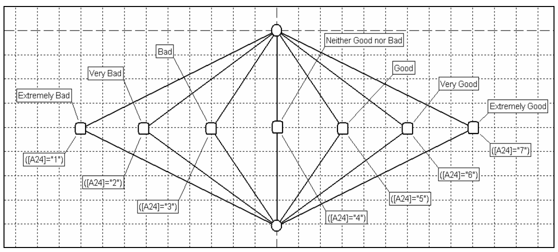
The main research instrument involved acquiring responses to work-place scenarios via an online survey questionnaire using a 7-point Likert scales as shown in Figure 1. Apart from a slightly similar method by Kollewe (1989), no evidence has been found for the use of FCA in processing survey questionnaire data. If we convert the Likert scale into a crosstable (figure 2a), similar to the approach used by Spangenberg and Wolff (1988), we see how the data presented in the rows represents the Likert value given in the diagram above. For example we note ([A24]="1") corresponds to a Structured Query Language (SQL) statement whereby A24 represents the column in the database table, and 1 equates to the value 'Extremely Bad' (remembering 1 referred to Extremely Bad through to 7 relating to Extremely Good). In creating and examining each formal concept lattice for each answer option for each scenario, we are slowly able to build up a picture for how novices have answered relative to that of experts. Figure 2b shows the data that has been taken from the crosstable (table 2a) and converted into a lattice. When the data from the questionnaire database is introduced into the lattice we begin to see how respondents have answered a single question and answer in the questionnaire.

The data visualisation can become even more sophisticated when using FCA. For example, in figure 3 we have used nested lattices to visualise both the ethical (outer ellipse) and realistic (inner ellipse) responses. The swing from bad to good noted in tables 1a and 1b can be seen here in greater number of experts on the negative side for the outer lattice and a greater number of experts on the positive (right hand) side in the inner lattices, as identified by the solid black dots. While the lattice does

Figure 2. (a) Illustrating the formal context (crosstable) and (b) corresponding concept lattice



2a: crosstable

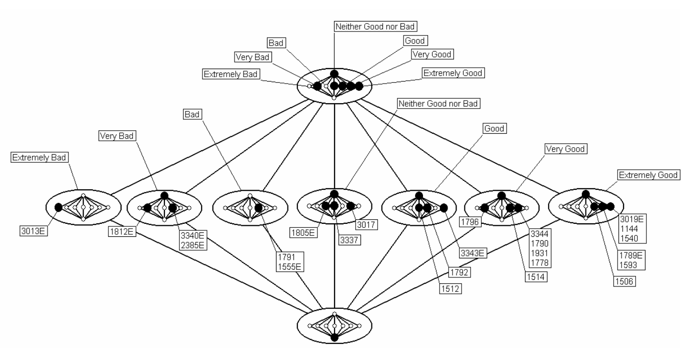


2b: concept lattice

Table 2. Illustrating the addition of the expert non-expert sample result into the expert sample

Ethical values only: difference between experts and novices in terms of how they answer the scenarios ethically
Null hypothesis: That there is no difference between experts (experts + expert non-experts) and novices in terms of how they ethically answer IT scenario tacit knowledge questions.
Statistical significance: ***z*** = -1.8 (with a 3% significance).
Answer: The null hypothesis ***can be*** rejected at the 3% level.
Realistic values only: difference between experts and novices in terms of how they answer the scenarios realistically:
Null Hypothesis: That there is no difference between experts (experts + expert non-experts) and novices with regard to *realistically* answering scenario related questions.
Statistical significance: ***z*** = -1.4
Answer: We cannot reject the null hypothesis.
Experts only: Statistical significance between realistic and ethical responses:
Null hypothesis: That there will be no difference between ethical and realistic values for the experts (experts and expert non-experts).
Statistical significance: ***z*** = -1.0
Answer: We cannot reject the null hypothesis.
Novices only: Statistical significance between realistic and ethical responses:
Null hypothesis: That there will be no difference between ethical and realistic values for the novices.
Statistical significance: ***z*** = -0.9
Answer: We cannot reject the null hypothesis.
Differences within each of the groups (novices and experts) and then determining the difference between experts and novices.
Null hypothesis: That there will be no significant difference between experts and novices in terms of how they answer internally within their scenario/answer combinations.
Statistical significance: *z* = -0.473
Answer: We cannot reject the null hypothesis.

Figure 3. Illustrating formal concept lattice for Scenario 10, answer 2



not show complete consensus amongst experts, it gives us a better feel than the use of means or medians. For example, for some scenarios the mean was 4.0 (Neither Good nor Bad) but the individual data points showed a complete spread from Very Good to Very Bad, rather than a lack of preference one way or the other. We can see that all novices, except for 1791, have found the answer option (that the client's happiness is all that basically counts) to be good to some degree. In contrast, 1791 had chosen to respond similarly to the majority of experts. By noting this similarity for all 125 answers (examining all concept lattices) novices can be listed in descending order of similarity with expert answer responses. Those novices with the greatest incidence of similarity with experts, head the list. Across the three organisations we added an extra 29 personnel who were able to be identified who had scored close to that of experts using the aforementioned technique, without necessarily being identified by their peers as being experts. Examining the closeness of the scores in descending order, it was decided the top 32% of ENEs warranted inclusion as a group, as this set appeared to present a natural cut-off point from those who scored below them.

Once we had identified the ENEs in each organisation, we returned to the question of whether experts and novices behaved significantly differently. The fact that some 'novices' were behaving like experts but not identified by their peers as experts, would account for the lack of significant results from the Wilcoxon test. Thus we re-ran the test but this time removing ENEs from the novice data and adding them to the dataset for the expert. Table 2 shows that we now get a statistically significant result, but only for the ethical responses.

DISCUSSION

The point of the exercise presented in this paper was not to explore the tacit knowledge management of three IT firms in detail. Rather we present an approach to data interpretation and explore the possibilities for data analysis using a couple of different techniques. The Wilcoxon test along traditional statistical lines permitted us to reveal that experts and others only differed 'substantially' in their results are far as ethical responses to scenarios were concerned. The point is that the statistical test here was based on only a small sample size. Furthermore the reduction of the data to numbers meant that much fine detail was lost. After careful examination of data through Formal Concept Analysis we were able to build up a picture on an individual level, of personnel whose responses were close to those of experts. From an organisational learning perspective this means we were through such a technique, able to identify other tacit knowledge rich personnel who can be called upon to pass on their expertise. A downside to our approach is that it is very laborious. For each of the scenario-answer options a formal concept lattice has to be drawn and then the answers of individuals examined. In other words rather than collapsing data down into numbers and manipulating data this way, the FCA approach we adopted meant exploring each answer individually and then generalising outward from here.

CONCLUSION

Data interpretation depends to a very large degree on sample size. Statistics tend to work well if the sample size is large. The downside to enumerating data is that much value is lost in this process. An alternative approach is to use graphically based techniques such as Formal Concept Analysis. The finer granularity of data interpretation used in FCA means the process does tend to be more data intensive, however the reward is that small sample sizes are not necessarily invalidated. We have provided an example where a data set from three IT organisations was used. The FCA process has also enabled us to identify through a very fine level of granularity, respondents whose answers were similar to that of the expert sample. In doing so we provide an example to organisations where they may wish to identify, in this case tacit knowledge savvy individuals, who may not have been so identified by their peers.

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