The Devil’s in the Detail:
Visualising analogical thought in retail location decision-making*

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Abstract

Retailers use analogues (similar stores) routinely in the process of site assessment, either as a basic method of sales forecasting in its own right, or as a check on more complex quantitative models. In earlier stages of our research, we identified ‘intuitive’ or qualitative causal knowledge structures derived from cognitive mapping interviews with UK retail directors to classify new sites according to their degree of likeness on these same attributes. Here, we focus on how the analogies identified by our qualitative system can be visualised effectively for use in location analysis. The paper discusses the role of analogy in retail location decision-making and the advantages and disadvantages of different methods of visualisation. We evaluate the visual aspects of the system developed in the course of our research with reference to users’ qualitative responses. The central issue appears to be the value users place on the system being able to summarise analogues simply on key dimensions at a general level, as well as its ability to ‘drill down’ to detail so that analogue representativeness can be established.

Keywords: Visualisation; analogy; site evaluation; retail location; intuition.

The range of what we think and do
Is limited by what we fail to notice
And because we fail to notice
That we fail to notice
There is little that we can do
To change
Until we notice
How failing to notice
Shapes our thoughts and deeds

R.D. Laing

INTRODUCTION

We know from previous management research that intuition enables managers to cut-through complex problems to the essence of a situation (Swink, 1995; Agor, 1989; Kleinmuntz, 1990; Showers & Chakrin, 1981; Payne, Bettman, & Johnson, 1988; Blattberg & Hoch, 1990; Molloy & Schwenk, 1995), and that the combination of intuitive insight with normative approaches enables decisions to be reached more quickly and effectively (Einhorn, 1972; Papadakis & Barwise, 1998a, 1998b; Spangler, 1991). Our research has shown how cognitive mapping can be used as a basis for pragmatically capturing the intuitive decision schemas of senior retail managers (Clarke & Mackaness, 2001) and integrated into a ‘composite’ map that reflects the understanding of the management group as a ‘bundle of influences’ on retail store performance (Clarke, Horita, & Mackaness, 2000b). We have also shown how this knowledge can in turn be used to cluster stores and enable analogues to be identified for new sites under consideration (Clarke, Horita, & Mackaness, 2000a). The purpose of doing this is to enable location analysts to effectively look at new sites through the eyes of experienced decision makers, focusing on the attributes they intuitively feel are important and using the vehicle of the analogy to ‘reflect’
their judgements back to them for consideration. The driving force behind our research is that, in cases where decision-makers want a rapid understanding of a situation, previous decisions can serve as source analogues to aid the current decision-making process (Holyoak and Thagard 1995), by enabling decision-makers to use analogical thought to create a ‘model in the mind’ and help make sense of a situation.

In order to assess the impact of this analogy-based system for harnessing qualitative or intuitive insight, however, it is critical that we are able, in the first instance, to visualise store analogies based on their key dimensions so that we can reflect these analogies back in a digestible form to retail decision-makers. The only meaningful way of judging the visual effectiveness of the system is with reference to retail users responses to the system we have developed. The current paper therefore outlines the implementation phase of the project that we proposed in earlier publications, focusing specifically on the visualisation of analogies derived using decision-makers’ thought constructs. We have now developed our ideas into a completed software package we call MIRSA AnalogueFinder 2.0, consulting with our participating retail organisations on practical and visualisation issues during its development. We draw off general user feedback on the visual aspects of the system to identify the issues retailers consider important. The first section of the paper considers the role of analogical reasoning in location decision-making within a retail environment and briefly outlines the process we have used to map and utilise retailers’ intuitive insights as a platform for analogical reasoning. Section two of the paper critiques the methods available for gathering and visualising qualitative data, emphasising the importance of information ‘chunking’ prior to use within the system. The analogue is utilised as the vehicle for moving between abstract generalisations and the details of the data in specific instances, the importance of which is the key point that emerged from our retail users.

THE ROLE OF ANALOGY WITHIN RETAIL LOCATION DECISION-MAKING

It is ironic that retail decision-makers appear to take a relaxed approach to the evaluation of new sites for store development, despite the financial significance of these investments (Brown, 1991; Hernandez, 1998). Given the substantial technical advances made in location modelling, why should this be the case? (Davies, 1976). Why should retail decision-makers continue to use their ‘gut feel’ approach? (Bowlby, Breheny, & Foot, 1984; Breheny, 1988; Clarke, Horita, & Mackaness, 1999a; Clarke, Mackaness, & Horita, 1999b; Hernandez & Bennison, 1999; Rogers, 1987). The answer most probably lies in the fact that the majority of retailers historically developed simple approaches to evaluate site potential rooted in their experiences of factors they felt were driving store performance. Experience entered site assessment procedures initially through the development of ‘rules of thumb’, where a combination of experience, empirical observation, and trial-and-error are used to isolate factors affecting sales performance (Jones & Simmons, 1990). Many of these relationships were accepted as reliable indicators without testing. However, Applebaum’s ‘analogue’ method (Applebaum, 1966) was the first to make the bridge between experience and empirical data, by balancing subjective judgement with quantifiable experience to provide benchmarks for the performance of a new stores with other stores in ‘analogous’ market conditions. The approach proved intuitively appealing because it responded to the question that inevitably comes from retail decision-makers, ‘where is this site like?’ The success of the method is heavily dependent on the skill of the analyst in picking analogies that they consider to be appropriate, whether it is being used to provide a sales forecast based on the assumption of a new store achieving comparable market penetration levels, or simply as a means to justify the outputs of other more complex location assessment procedures, such as regression or spatial interaction models (Ghosh & McLafferty, 1987). Invariably, the
method depends partly on quantified experience and partly on subjective judgement (Applebaum, 1966), so it is perhaps not surprising that a tension exists in group decisions in retail organisations between the outputs of formal statistical approaches and the ‘intuitive feel’ of decision-makers themselves (Penny & Broom, 1987), essentially because the quantitative models are unable to recognise the full complexity of real-world problems, which require a rich understanding of the trading environment and competitive conditions locally (Ghosh & McLafferty, 1987).

The popularity of reasoning by analogy in retail organisations is not surprising. A term coined by (Steinbrunner, 1974), ‘analogical reasoning’ involves the application of simple metaphors or images to guide the definition of a problem – a very different approach to the positivistic stance of most strategic decision-making (Baumard, 1999). Thus, whilst reasoning by analogy provides an extremely useful approach to knowledge by interpretation (Polanyi, 1966), the problem is that decision-makers ‘may not objectively evaluate the extent to which their analogy is representative of their decision situation’ (Schwenk, 1984, p.118). In terms of site location assessment, the main difficulty is that one of the main features of the analogue method to site evaluation is whether or not to pick the closest analogue – with the risk that the analogy is not comparable in every respect – or to compare it to the averages of a number of stores, with the all central tendency that the latter implies (Ghosh & McLafferty, 1987). Whilst other researchers have attempted to remedy this situation by constructing a retail location model based on managerial judgements (e.g. Durvasula, Sharma, & Andrews, 1992), the predictive measures they use are arguably too dependent on accepted influences derived through the normative literature, rather than adopting a grounded view and looking towards the managers experiential inputs as a starting point. What we propose is to describe analogies for new sites in terms of how experienced retailers might see them, a process which is designed to act as a check on existing normative evaluation methods.

In our earlier papers we outlined how we have used cognitive mapping to construct an understanding of the decision schemas of retail executives. Based on Kelly’s theory of personal constructs (Kelly, 1955), cognitive mapping is a technique that has been used widely by management researchers in a variety of different contexts (Ackermann, Eden, & Cropper, 1990; Bougon, Weick, & Binkhorst, 1977; Calori, Johnson, & Sarnin, 1994; Carlsson, 1995; Eden, 1993; Klein & Cooper, 1982; Tolman, 1948; Wang, 1996). The mapping process involves respondents identifying factors affecting or causing a particular decision-making ‘goal’, related in a causal (‘means-ends’) fashion. We utilised it to tease out the implicit dimensions of decision makers’ schemas by interviewing senior directors and managers of three national UK retail multiples. Respondents were encouraged to think about the key factors that they felt influenced the stores’ sales performance – factors that were elaborated using a laddering interview technique. For each organisation, the resulting cognitive maps were merged using constructs they had in common, into a single composite map (see Clarke et al., 2000b for further details) – with any duplication between them systematically removed. From the resulting composite map, a collection of data reflecting these influencing factors was constructed. It is this collection of data that we used within the system to choose appropriate analogues for new sites.

To define our data requirements, each composite map ‘tail’ concept was considered to be a potential qualitative measure. For instance, in the anonymous company we utilise as an illustration in this paper, a complete list of 123 tails was compiled, indicating each measurable factor that was suggested by the respondents. However, it is neither desirable
nor practical to collect data for every tail construct recorded. For example, those constructs falling under the head concept of ‘service delivery’ (e.g. quality of store manager etc.) were intentionally excluded as it is not possible to predict these for a new site as they are highly variable between analogue stores. A list of the remaining constructs was then given to the Site Research Manager who was able to determine those constructs for which the store had data readily available. Further liaison helped to identify those constructs that could be measured, but for which no data was currently held. The retailer’s Site Research Team then undertook data collection for these remaining variables and a final set of data was provided in tabular format. For the company we illustrate here, a total of 60 ‘conforming’ stores (those of essentially the same format) across the United Kingdom were identified and used as the data set.

**VISUALISING ANALOGIES**

Over 120 possible variables were identified to assimilate and classify each analogue store. The next task was how to meaningfully distil this information to those involved in retail decision-making, without losing the nuance and detail that the qualitative information contained.

Based on conversations with the retailers, we saw a need to find compromise between providing an overview and providing overwhelming amounts of detail. It is necessary to strike a balance between these two levels of detail in order to facilitate exploratory data analysis. In considering different levels of detail, Tufte argues that macro and micro readings are powerful tools allowing users to access vast amounts of data through hierarchical layers (Tufte, 1990). He suggests that detail cumulates into larger logical formations which, when properly arranged, add to the simplicity of comprehension. The underlying detail (micro information) ‘provides a credible refuge where the pace of visualisation is condensed, slowed, and personalised’. (Tufte, 1990, p.38). Similarly, Kumar and others discuss the need for querying different levels of hierarchical data sets (Kumar, Plaisant & Shneiderman, 1996). Here, trees are dynamically queried and uninteresting branches of information are pruned, leading to compact views of relevant information. Even early work by Miller suggested that the grouping of similar details into larger chunks is a useful device for increasing our capacity to process information (Miller, 1956). Furthermore, Miller notes that there are limits on our capacity for processing information and that this constraint is usually found to be close to seven categories. Within our composite map for this one retailer see (Clarke et al., 2000b), it is possible to discern eight distinct heads or data ‘chunks’, as illustrated in simplified form in Figure 1a. The variables falling beneath these heads in the original composite map (Figure 1b) were ‘chunked’ into groups accordingly. For example, all constructs falling below the Market Size head were recoded together and this collective section of the composite map was then coded as ‘Market Size’.
Having obtained and structured the qualitative data within this ‘hub’ formation, our concern was with being able to use this to identify groupings or clusters of similar stores using the detailed qualitative attributes. The literature on this broad area of ‘pattern matching’ shows that the field of data analysis can be loosely divided into two levels of data analysis: exploratory and predictive (Hoppen, Klawonn, Kruse & Runkler, 1999). Our objective is to focus on the former – in terms of the frequencies and recognition and reporting of patterns within the store analogue data. We place special emphasis on interactive exploration of the data using visual displays to reveal vital information about the data being examined. The basic philosophy underlying these techniques is one of searching, with stress placed on the
use of alternative techniques to assess the same body of data (Malczewski, 1999). Justification for effective visualisation of this information is provided by research into heuristics – the psychology of groups and individuals in decision-making – which shows that there is a tendency for individuals to simplify tasks for five main reasons: they find it difficult to recall information; they introduce bias when reflecting with hindsight; there is a tendency to take particular cases out of context; they make relationships between data that does not necessarily exist; and there is a tendency to accept judgements that are not ‘representative’ of the group as a whole (Simon, 1957; Tversky & Kahneman, 1974; Fischhoff, 1975). The result of these tendencies is that bias can result in decision-makers being overconfident in their judgements (Fischhoff, Slovic, & Lichtenstein, 1977), a tendency which exploratory interaction of the data can help overcome. Our rationale is that representing clusters of stores, with a transparent rationale for these groupings, will aid retailers to surface and discuss their individual biases.

There is a host of techniques that can be used to identify patterns in data and clarify the complicated mechanisms of decision-making (Everitt, 1993; Fukunaga, 1990). Multivariate classification, methods of unsupervised learning, and other statistical approaches are some of the methods we considered. The method we chose was a combination of c-means and c-modes clustering. Our justification was that whilst this choice does not allow cases to be represented in multiple groups because of their common characteristics, it enables use of multiple data types, including real-value, integer and categorical, which the alternatives methods such as fuzzy Kohonen networks, self-organising maps, competitive learning, and genetic algorithms are less capable of dealing with because of the limited granularity of some of these data types (Fukunaga 1990; Mitchell 1996; Zeidenberg 1990). We discuss these issues in greater depth elsewhere (Clarke et al., 2000a), but here we focus on the two forms of cluster analysis, each of which combine multivariate analysis with techniques of unsupervised learning: crisp and fuzzy clustering. Both were initially considered as methods for grouping retail stores. The aim of traditional crisp cluster analysis is to partition a given set of data or objects into clusters (also referred to as subsets, groups, and classes). This partition should ensure homogeneity within the clusters and heterogeneity between clusters. Conversely, fuzzy clustering dispenses with crisp assignment of objects to classes, and instead computes degrees of membership that specify to what extent each object belongs to each cluster. Assignment of objects in conventional crisp clustering is always to the nearest cluster, with 100% membership to one cluster and 0% membership to all others. With fuzzy clustering membership values may range between 0% and 100%, where each object can have a degree of membership in each cluster (Duda, 2001).

Visualisation is an essential part of exploratory data analysis. In using different methods of visualisation, it is possible that new clusters may be revealed or that new information may be extracted. The challenges of visualisation in the scope of this work are characterised by the need to impart both qualitative and quantitative data in a straightforward and meaningful manner. A number of visualisation methods were considered with reference to crisp and fuzzy clustering. First, the use of simple ring charts is effective in illustrating the percentage of membership that stores have to each cluster. Figure 2 demonstrates how the degree of membership can be visualised, by illustrating eighteen stores that have been grouped into six classes using fuzzy clustering. This method of visualisation is useful for gaining quick insight as to the composition of the clusters. For example, it is apparent that cluster groups A and C are dominant in terms of accounting for the degree of membership. The ring chart provides an ideal summary of the cluster formation; however, no information is supplied to help the user determine the detail ways in which the stores are either similar
or different, a feature that the company found to be a distinct weakness of this form of visual representation. An alternative cluster visualisation has its roots in spatialisation – a visual representation of textual information in a context of space (Skupin, 1999). It uses the metaphor of a topological map to show how documents or objects are related to one another. ‘Themescape’ (Wise et al., 1995) reads large collections of documents and organises the content by topic as a topographical map. The example, shown in Figure 3 shows stores as dots that are labelled with the store’s identification number. Similar stores are placed close together forming peaks, while dissimilar stores are located at further distances forming valleys. The benefit of using the topological metaphor is that it enables the map-reader to quickly identify groups of similar objects without knowing anything about the attributes of individual objects. Users can gain further information about a particular object by clicking on the map to open a text document that describes its attributes, so in this case the detail of the comparisons is accessible, if not immediately viewable.

Figure 2: Using ring charts to visualise fuzzy clusters

Figure 3: Themescape's topological metaphor
Feedback from participating retail organisations indicated both methods of visualisation adequately portrayed the similarity between stores, though ThemeScape was preferred because, in the words of the Site Research Manager: ‘it more clearly shows the relationship between stores and how close together they are’. Further discussion revealed that it was important for the user to be able to readily access the underlying data so that they could ‘drill down’ into the detailed characteristics of each store. A major drawback of Themescape is that it uses word recognition from text, rather than object-orientation, so its use was not practical. Options for exploration of the data using these visualisation methods was limited, to a large extent, by the qualitative format and granularity of our data. From further discussion with site research managers, it became clear that crisp clustering (and its associated visualisation techniques) was a more manageable and more readily understood form of grouping analogues. A number of methods of visualising crisp clusters were considered, with the goal of illustrating the differences between analogue stores that are grouped in the same cluster. Consideration was given to the use of a superposed ‘spider diagram’ (Figure 4), inspired by a traditional quantitative method of visualisation, the star diagram (Chambers, 1983; du Toit, 1986; Everitt, 1993) and the works of Noirhomme-Fraiture (2000). Here a variety of qualitative and quantitative attributes are represented in a radial style chart that focuses on variables such as size and shape. With a similar technique applied to the store data, a different coloured line was used to represent each analogue store, with the selected store symbolised by the black central circle. Again, each branch is representative of one of the eight hubs used in the recursive clustering process. The distance at which the coloured line intersects each branch shows the analogue’s similarity to the selected store. An intersection close to the central circle indicates a high degree of similarity, while an intersection at a further distance from the centre suggests a less similar analogue. The axes have intentionally been left without scales so that users do not attempt to attach quantitative meaning to the dissimilarity values. The use of superimposition can be dangerous because in a superimposed image, the eye can only see the form created by the sum of the characteristics (Bertin, 1981). Since the sum is not meaningful in this case, the overall form is without significance. A more suitable representation was to represent each store in its own chart, as we will discuss in the next section.
The recursive-clustering algorithm implemented in MIRSA AnalogueFinder 2.0 combines two methods of crisp clustering. In the first stage of clustering, the c-means algorithm is used to group individual variables based on the ‘hubs’ defined by the user. The c-means algorithm is a non-hierarchical method of classification that initially takes the number of components of a population equal to the final required number of clusters. Simply stated, this algorithm partitions the variable data so as to minimise the sum of the squared distances to the cluster centres. The second stage of the recursive-clustering process makes use of the c-modes clustering algorithm, in which the results of the first clustering stage are clustered further to group stores into a ‘overall’ cluster. The c-modes algorithms extends the c-means algorithm by using a simple matching dissimilarity measure for categorical objects, modes instead of means for clusters, and a frequency-based method to update modes in the clustering process to minimise the cost function (Kaufman, 1990). The overall result of the clustering process is that each store/site is assigned to a certain cluster for every key issue or ‘hub’, and this cluster membership is then used as an attribute for the final level of clustering into an ‘overall’ cluster.

The clustering process as described above is useful in helping to identify which stores are different by grouping them into different clusters. However, as discussed earlier, if we are to enhance the analogue approach by evaluating the degree of representativeness of the analogue to the site, it is also necessary to illustrate to what extent stores in the same cluster are either similar or dissimilar. In order to make this assessment we have employed a Euclidean distance measure of dissimilarity that allows us to calculate a dissimilarity value for each analogue and the selected store. This measure of dissimilarity is strictly a relative value and does not hold specific quantitative meaning. The output of the clustering algorithm is simply a table of characters which denote to which class each store belongs based on the eight individual hubs and based on an overall assessment. This cluster matrix coupled with the calculated dissimilarity values help to indicate the extent to which two

Figure 4: Four superposed spider diagrams
stores are similar (see Figure 5). Neither method is particularly helpful in understanding and interpreting what the cluster results mean, however. By providing tools to further explore the data visually, users can begin to understand the clustering process and can assess the value of the results. The challenges of visualisation come when trying to illustrate the differences between stores that are grouped in the same cluster. This is an important step in helping users to explain the patterns produced by the clustering algorithm and evaluating the value of the resulting groups of stores. Although the calculated dissimilarity value goes some way to explaining the extent to which stores are similar and different, it does not help to uncover what these differences might be.

Figure 5: Dissimilarity of analogues to site, showing ‘hub’ dimensions

The ideas of star diagrams discussed in the previous section was developed into the spider chart representation that is shown in Figure 6. In this final hybrid method of visualisation, the concept of the superposed spider diagram has been simplified so that each analogue is charted in its own window, in order to eliminate the confusion of overlapping lines. Additionally, each polygon denoted by the coloured lines was in-filled in order to give emphasis to the overall size and shape of the graph. Size and shape have also been identified by Bertin (1981) as belonging to the group of eight visual variables and are noted as helping to convey variation between images. In the example below, the size and shape of the graphs are indeed important. First, the overall size of the filled polygon conveys the degree of similarity between the selected store and the analogue (a smaller filled area represents a close degree of similarity). Second, the shape of the polygon summarises in which ways the analogue is similar or different from the selected site. For example, looking at the green chart we can see that Huddersfield is somewhat similar to Exeter in most respects, but very different with regard to store format. Indeed this is a useful method of quickly illustrating how otherwise similar groups of stores are different.
DISCUSSION: USER RESPONSES

At this point in the development process, we presented the MIRSA system visuals to three senior managers, each of whom either undertook or worked in close association with the site research function within one of our participating retail organisations. The purpose of this meeting was to gain an initial validation of the visualisation features, and to help further develop these measures. The presentation took place in two stages. First, an initial meeting that presented the model as still ‘visuals’ – essentially those described and illustrated above – and two months later, a second meeting to demonstrate the complete live model, prior to its installation and use within the company in a real decision-making setting. Both discussions took place in a group setting with four of the Company’s senior executives present. The meetings were taped and transcribed and in the following discussion, we draw use excerpts from this text to assess the acceptability and value of the visualisations to the users.

In the initial presentation – following a period of assimilation and clarification of what each of the visuals showed and how they related to each other – there was apparent surprise that the system readily summarised what the respondent managers felt were the key drivers of store performance. They felt the system was important and valuable because, as one manager put it:

People can't usually handle more than a couple of variables at any one time. We typically simplify things and focus on a few known factors. This [dropping variables that seem insignificant] can be dangerous for us because we are never one hundred percent certain that these factors are not key drivers.

Despite the fact that all those present were themselves respondents who had been interviewed during the cognitive mapping stage of the research, and therefore understood our desire to develop an approach that focused on their own insights, the surprise at the apparent transparency of the system was clearly evident. Moreover, the above statement reflects their immediate evaluation of the overall objective of MIRSA, to provide a balanced overview of each site and a reliable basis for ensuring that all factors are taken into account in the process of decision-making, rather than what they were implying was a current
tendency within the Company to rely on one or two key factors, which they felt could be misleading in some circumstances.

Presentation of the ‘spider’ diagrams (Figure 6), which highlighted the four closest analogue stores to the comparable details of a new site, also generated a favourable response. Looking at the list of chosen analogue outlets, one manager, musing over the comparisons, initially looked reluctant at what the output was saying, but then, picking one of the chosen analogues, admitted that he ‘would never have thought of that one!’ Another respondent went onto say that he felt that:

This is an interesting way of illustrating the information from the data. These charts would be helpful when comparing two stores… Although the shape [of the polygons on the charts – see Figure 8] may be very different, the area [amount of colour] clarifies which analogue is the closest.

Subsequent discussion of the comparisons thrown up by MIRSA, however, led to some disquiet and it became evident that there was some disappointment with the system in its current form. The reason for this is summarised in the following statement:
Yes, it is a good way of visualising, but we definitely need a finer level of detail. We need to think about the dimensions being measured. What are the differences between the store and the analogue? We need to get a level below this, in terms of detail, so that we can explain why two stores are different. We need to understand the data...

Further discussion forced the respondents to elaborate on the reasons for this apparent frustration. It emerged that, whilst the ‘spider’ visuals emphasised the main dimensions underlying what they regarded as the successful performance of new stores, the group immediately wanted to delve further into the detail of the underlying data behind the comparison, so that they could explain in what ways the analogue was either comparable or different from the new site. One manager made a suggestion as to how this might look if the system was developed:

Perhaps, if you could click on one of the eight ‘spokes’ to display another similar diagram of just that specific variable, in order to explain where the differences are. If we can't do that, then we automatically lose credibility!

It emerged that what was behind this latter reference to ‘losing credibility’ was the site research team’s close working relationship with other functions within the company’s Head Office, especially the Finance department. It became evident that, without the ability to explain the choice of analogue and, by implication, confirm or refute the sales forecast provided by their own quantitative model, the Site Research function’s standing internally would be immediately affected. Although the ability to summarise and identify the key features of comparable analogues stores within the system was important, the team felt that they would, effectively, be ‘shooting themselves in the foot’ without being able to justify the comparison further. The ability of the specialist Site Research function to explain its reasoning was clearly important in terms of the internal working politics within the organisation.

Another interesting tension was also induced by the visual representations of the MIRSA model. Whereas the Site Research Manager, with whom we had been working closely in the development of the model, could see the value of the system in its own right and was prepared to work at understanding the analogues it identified, for the other respondents, there was clear unease about what the system was saying about the outputs from their own well-developed quantitative ‘gravity’ modelling system. Discussion in the meeting centred on how any differences between the sales performance of chosen analogues identified by the qualitative MIRSA system and the company’s own forecasting model could best be rationalised. The most senior executive asked:

…how do we compare the similar stores to the outputs of the gravity model?
I feel like I'm missing some steps.

And another manager commented:

We need to be confident we can assess and explain the differences between the results from the two models. How do we evaluate the worth of the information coming out of this [MIRSA] system?

Finally, the first executive added:
We need to be able to explain where the differences are and what they mean. We need to bridge the gap between the MIRSA model results and our gravity model results.

Clearly, whilst as outsiders we were prepared to position the system as a stand-alone alternative to sit alongside their existing highly quantitative model, the Company needed to be able to conceptualise how the very different qualitative approach – grounded in the insights of their own executives – could be brought together with their own quantitative model. It was difficult for them to refute what MIRSA was saying, as the model output was, in effect, legitimated as a result of being based on their own insights. Nonetheless, any potential gap between the two approaches was a source of discomfort to those present. The executive present articulated this issue, which he saw simultaneously as a problem and a useful avenue for them to think along that might help the group to arrive at a solution. For example, he said, if the analogues identified by MIRSA, in terms of their features and performance, were in line with their existing quantitative model, then there was essentially no problem. There were two other scenarios, however, which could prove problematic: where MIRSA provided a convergent set of very similar analogues, whose performance was substantially different from the quantitative model; and where the quantitative model output was seemingly validated by the sales performance of one of the analogues, but not by the others. Once again, it became evident that if the system was to be accepted and used within the Company, then it was clear that the ‘bridge’ between the two approaches was going to lie in our ability to visualise similarities and differences between the analogues and sites under consideration in terms of the detail of each dimension or ‘hub’ of comparison – there was a need to be able to interact between the general and the specific levels of analysis. With these issues in mind, we undertook further development of the MIRSA system over a period of two months, prior to a second presentation to gather additional views on the visual aspects of the system and its installation within the organisation for use in ‘live’ circumstances.

At this time we began to search for ways of providing further visualisation that would help users to explain the differences highlighted by the system between sites and the analogue stores. For example, what characteristics make Huddersfield so different from Exeter based on the ‘store format’ hub of qualitative data? What was of concern to the respondents within the Company was the question whether it is reasonable to accept any different ‘opinions’ that MIRSA helped to generate within the decision-making group. In such circumstances, are any potential differences due to error within the qualitative MIRSA approach, or is it the quantitative model that is ‘at fault’? To address these types of questions we developed and implemented further exploratory data assessment functionality, the essence of which was to undertake further coding that enabled detailed comparisons of individual analogues with the site being considered.

System modification driven by user feedback is illustrated in Figure 7, which provides a more detailed level of comparison. In this example, let us assume that Wallasey has been highlighted as the closest analogue store to the Edinburgh site, in all respects with the exception of the ‘Performance’ hub. Highlighting the latter on the spider diagram would now illustrate the detail underlying the differences between the two in this respect. If the Company’s quantitative model is suggesting a similar sales figure on the Edinburgh site to the Wallasey store, then examination of the data might lead them to doubt their own model output, because the detailed comparison shows that the level of home ownership and ‘high-spending’ do-it-yourself shoppers (in which sector the Company trades) are much lower in
Edinburgh. All other things being equal, therefore, the MIRSA analogue output might suggest that the decision-making group would need to be more cautious in their investment decision. Conversely, if these same measures had been higher in Edinburgh, then this might tend to suggest to those making the decision that they could afford to be more optimistic about the trading potential of the site than their quantitative forecasting system indicates.

Finally, we purposely ‘linked’ the outputs of the Company’s own data and approaches on each analogue store, to the outputs of the MIRSA analogue analysis, in the form of a ‘scatterplot’ (Figure 8). Within this representation, the chosen analogues shown in the visualisation shown in Figure 6 are emphasised in the same colours. We felt that this form of visualisation would be useful for three reasons. First, it draws attention to the difference between the Company’s own quantitative assessment of each of the analogue stores’ potential sales and the actual sales. Second, pop-up windows emerge as a ‘roll-over’ function for each of the analogues, making Company data readily accessible. Finally, it underlines either the ‘spread’ or ‘convergent’ nature of the closest analogues identified by the system, drawing attention not only to the dimensional differences between the site and the analogues, but also to how some of the qualitative attributes might help to explain their own quantitative models ‘accuracy’ in each case.

Once these changes had been made, we subsequently undertook a live demonstration of the MIRSA system to the same management group. They were taken through each of the visual elements in order, using the details of the Company’s Edinburgh superstore as a mock ‘site’, in the way same way that the system would be used for a new development. Thus, the only difference in this instance was that the actual performance of the outlet was known. We outlined to the group how their previous concerns about being able to access the detail of comparisons, plus the bridging of the gap between the MIRSA output and their own model, had been addressed. Reaction to the new visualisations was immediate, with the Property Development Director noting that:

…if you said to any group of people, ‘we are thinking of Edinburgh, from the point of view of accessibility, name four stores in the current chain that most similarly replicate the access and situation that we have got at Edinburgh’, I’d lay my mortgage on the fact that Stockton would not be one of them, and yet, based on the criteria we have set, the mind maps that we have used, Stockton has come up being one of them. And I know its
subjective, and everyone is going to have a slightly different view, but I just don’t think it would be in the same category…

Interestingly, it emerged that this final note of scepticism centred not on the MIRSA system, but on the adequacy of data supplied by the Company, as measures of the qualitative ideas (‘tails’) in the composite map. He went on:

…obviously, part of working with the [MIRSA] model will be to review the input data…or it may suggest that my perception is wrong…that Stockton is, in fact, very similar to Edinburgh…”

In fact, this theme of the adequacy of the data supplied by the Company was a recurrent theme of the ensuing discussion, centring on how insight could be improved with more considered surrogate measures of the intuitive constructs. Clearly, this quote also illustrates the awareness of using intuitive insights provided through MIRSA to question the Company’s quantitative model, by assessing the degree of similarity / dissimilarity of the site compared to the individual analogue stores.

However, it was evident that there was still a prevailing concern about how the qualitative ideas would be interpreted within the Company and what this meant for the way forward in terms of its use inside the organisation. This concern was illustrated in the following statement from one of the managers present at the meeting:

…we think we are experts and relative to the rest of the business, we are. If you were to take a group of store managers and have this debate, you’d be all over the place, ‘cos their view of what’s good accessibility and what is bad accessibility, is just like, off the Richter scale, because that is not in their training, or their thinking. I mean, they are acting on intuition and some of them will recognize a good site from the point of view of accessibility from the outset…and we have had others who say, that a site we know is well-accessed…and they’ll say accessibility is poor, and that’s the reason it is not trading well. So it all depends on what group of managers you are addressing for these questions, and if we get this level of debate in a so-called ‘expert’ group, goodness knows what would have happened in the wider group.

The concern here was evidently with the differing interpretations that were possible of the qualitative information made accessible by the analogue comparisons, to a wider group of managers. The implication was that the Company would need to think carefully about how the approach could be used to nurture and develop a wider and uniform understanding of the factors that led to store success, albeit that this was a two-edged sword because of the possibility of misinterpretation if this process was not undertaken properly.

Ultimately, the real value of the visualisation system was seen to lie in terms of the effect it had on promoting discussion within the group, because of how it had been developed in response to the managers’ earlier concerns about how to ‘bridge the gap’ between the Company’s quantitative model and the insights provided by MIRSA, especially by being able to provide an overview comparison, as well as an understanding of differences between site and analogue store on any of the ‘hub’ dimensions. The Director noted that:

I think we have seen a significant improvement in terms of where you have got to…there is some real usability inherent in this system. Just in terms of the debate it generated that we have had today…but I am also conscious that it is still very much work in progress…because of the quality of the data that
we used to put in initially and thinking moves on, and partly because, you
know, we are having these other ideas that come into the conversation…

He elaborated further, illustrating at length that the value of the visualisations – despite the
shortfall in some of the measures since these could readily be resolved by the Company
developing more robust surrogate measures of the intuitive constructs in the composite
maps – was in its ability to promote a questioning of the existing quantitative approach
made by the organisation, with the aim of reaching better decisions:
…see, the ‘gravity’ model is hopeless in terms of predicting Edinburgh’s
turnover…and I am just wondering, does this [intuitive] data help us with
retrospect…’cos that’s exactly how we want to use this data, say it either
actually supports the gravity model figure or let’s question the gravity model
figure because there are some other things going on here…

Well, we’d be sitting here, wouldn’t we, with a gravity model figure for
Edinburgh of £19m, and the question we should be asking ourselves is that,
using this model and this [intuitive] data, is that gravity model figure a sound
one? It’s saying that, of the four stores that are most similar, to Edinburgh,
three of them are trading very closely to their gravity model number…and
therefore, this data, would be leaning us towards the conclusion that the
gravity model number was fairly robust at £19m, which with the benefit of
the knowledge that we have got [because the store is trading and its
performance is known] is actually the reverse of the conclusion we want it to
draw for us, which is that Edinburgh substantially outperforms the gravity
model figure. So, I don’t know what we blame…

The reason for this apparent discomfort was that, had the Company had the system when
considering Edinburgh as a site, they would have been able to use it to weigh up the
representativeness of site versus three of the analogues, against what appeared now to be a
closer analogue, because with the benefit of hindsight, the site had some of the
characteristics of the single analogue that seemingly went a good way to explaining why the
store had substantially out-performed their own quantitative model.

In this paper, we have shown how a new approach to an old method can be used naturally to
harness and communicate intuitive insights derived from retailers’ real-world experiences,
back into the decision-making group. The visualisation approach we have used has the
advantages of being linked to a familiar method, as well as being transparent. Judged by
comments from the users, the visualisation appears to be very acceptable for use in a real
decision environment because it does three things: it provides an overview of the degree of
similarity / dissimilarity for analogues to sites, based on dimensions grounded within
respondents’ own insights; it allows the user to explore these comparisons by accessing the
detail of the constructs; and, related to both these factors, it allows the group to come to a
reasoned assessment about the representativeness of these individual analogue comparisons.
It should, therefore, help to promote much greater debate around this particular type of
strategic investment decision in retailing and, in the process, help decision-makers to more
effectively weigh-up the risk and uncertainty surrounding individual investments. As the
intuitive analogue system is not, in our system, reliant on the location analyst to choose the
analogue store for comparison – as is the case with the original analogue approach – it is
likely that this will lead to a better understanding and appreciation of retailers’ intuitive own
insights.
CONCLUSIONS
Having previously developed an approach that can ‘tap into’ retailers intuitive insights regarding site location and demonstrated in this paper that these insights can be effectively visualised for retailers to use within their decision-making, it remains for us to test the veracity of the system by using it in live business environments. During the final implementation stage of our research programme, we will observe how the MIRSA system is utilised by each of our three participating retail companies as an aid to their decision-making processes. Clearly, this empirical testing of the value of intuitive insight will also have to be qualitative in nature, and will need to be sensitive to the ‘unfolding’ (Chia, 1994) of decisions as part of complex organisational processes and meetings, the essence of which we will need to capture using a variety of qualitative methods such as observation and recording of group meetings, user-diaries, and reflective feedback over the longer-term. From the initial insights of this paper, it is also clear that this evaluation will need to be sensitive to the internal organisational politics surrounding information and its use in decision-making – the key to the effectiveness of the system will be in its acceptance within the real ‘bombsite’ of decision-making (Eden, 1993), rather than an academic ‘laboratory’. Judged by the evaluation of the system to date, that ‘real world’ effectiveness will depend on the ability of the new system to help decision-makers assess the degree of representativeness of each analogue, by moving iteratively between the comparison overview it provides and the underlying evaluative components. In site location, just as in other decision-making situations, the ‘devil’ appears to be, very much, ‘in the detail’.

REFERENCES


