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Multivariate statistics in industrial marketing management: A practitioner tool kit

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Abstract

Much published work over the years has pointed to the differences between business-to-consumer (B2C) and business-to-business (B2B) marketing. An undesirable by-product of this sometimes misdirected distinction is that managers working within B2B environments have generally not considered the use of what are seen as B2C techniques, such as multivariate statistical analysis. This article is structured in three parts. First, the argument for the similarities between B2B and B2C marketing is developed; second, three different multivariate statistical techniques are presented and combined to form a practical tool kit for use by B2B managers on strategic, operational, and tactical levels; and third, the results of an application of the techniques in the life science research chemicals industry is reported, demonstrating that the tool kit substantially enhanced managerial understanding of customer decision processes.

Keywords: Multivariate statistics; Practitioner marketing; Life science

1. Introduction

As any perusal of the appropriate journals indicates, the use of quantitative methodologies in business-to-consumer (B2C) marketing has been widespread for decades, while business-to-business (B2B) marketing has not embraced these techniques to the same extent. This is in part because of the assumption that B2B marketing is fundamentally different from B2C and the resultant reluctance to "borrow" B2C techniques. We argue that in many industries there is much to be gained by accepting the similarities in the two disciplines and thereby considering some of the multivariate techniques developed to enhance consumer understanding. This article shows how a tool kit of multivariate statistical techniques can be used together to give B2B marketers a competitive edge on three levels: strategically, operationally, and tactically.

The tool kit discussed here consists of conjoint analysis, cluster analysis, and correspondence analysis. Conjoint analysis illuminates complex decision-making processes in multiproduct, multisupplier contexts and can thus be used to inform overall marketing strategy; cluster analysis, which segments buyers into groups with similar needs, enlightens operational resource allocation decisions; and correspondence analysis, which displays cluster information in two-dimensional space, can produce a visual aid useful for tactical sales training.

We have structured this article as follows: firstly, we briefly review the debate on similarities and differences between B2B and B2C marketing; we then discuss the mechanics and applications of each of the three multivariate statistical techniques separately and together; finally, we demonstrate how the tool kit has been successfully applied strategically, operationally, and tactically in the life sciences industry.

2. B2B and B2C marketing: the same or different?

In a management context, buyer behaviour is typically not considered as a single area of study but as two distinct

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subsets, consumer buyer behaviour and organisational buyer behaviour (Fern & Brown, 1984). This distinction results from the perceived differences between consumer and industrial markets suggested by many textbooks (Kotler, 2003; Wilson, 2000).

The fact that the differences have been promulgated for over a quarter of a century has almost certainly had an impact on the lack of inclination to use statistical techniques in organisational marketing. Three factors may have contributed to this phenomenon. First, many statistical techniques and principles are based on the central limit theorem, whereby many sampling units are all assumed to be of equal importance. With many B2B markets typically composed of a few buyers varying radically in their importance to the seller, it is easy to see why the relevance of statistics might not be immediately apparent. Second, if the relationship between organisational buyer and seller is assumed to be close—even personal—then the significance of impersonal mathematical aids is not obvious. Third, if the buying process in organisations is influenced by several parties, and if at least some of these are trained professionals, then the application of tools designed to understand individual decision-making psychology may seem quite inappropriate.

However, several writers have questioned the validity of the B2B–B2C distinction. Shaw, Giglierano, and Kallis (1989), for instance, observe that organisational buyers and consumers are in fact the same set of people only in different buying situations. They go on to ask, "Are we to believe that an executive makes business buying decisions based on quantifiable product characteristics and yet makes personal buying decisions based on intangibles?" (p. 45). Wilson (2000) poses the question, "Why should we assume that separate theories are necessary to explain the exchange behaviour adopted by the same individual when placed in different contexts?" (pp. 780–781), concluding that "it is debatable whether or not the surviving differences between organizational and consumer marketing constitute a sufficient or worthwhile basis for continuing a distinction at a theoretical level" (pp. 794). Concurring views are advanced by Foxall (1981), who writes "Industrial buying behaviour differs from that of final consumers not so much in kind as in degree. The stages, which comprise the respective decision sequences, are broadly similar" (pp. 135), and by Brown (1984), who contends that "practical experience and considerable research tell us that many of the individual/subjective influences [that shape consumer buyer behaviour] are also evident in organizational purchasing situations" (pp. 12). Furthermore, these views are not restricted to a belief that consumer and organisational buying are *broadly* similar but that *specific* elements of consumer and organisational buyer behaviour are also comparable. For example, Shipley and Howard (1993) consider only one aspect of organisational buyer behaviour, the impact of branding, but conclude that its application in the contexts of consumer and organisational buying behaviour is similar.

The central thesis underlying these views is that the two concepts of consumer and organisational buyer behaviour represent "extreme examples" rather than normative, generalisable models, which "although they do exist, tend to obscure the more basic similarities between industrial and consumer marketing" (Fern & Brown, 1984). We propose, in agreement with Fern and Brown, that buyer behaviour be viewed not in terms of these two extremes but rather as a continuum against which any of the theories of buyer behaviour may be more or less applicable.

3. When can multivariate statistics be applied?

If we accept that organisational buying behaviour is different from consumer buying behaviour in degree rather in form, then it is important to ascertain in which organisational buying contexts it is appropriate to use multivariate statistics that have ostensibly been designed to measure facets of individual decision making. Sheth (1973) provides a useful framework in his assertion that "organizational buyer behaviour consists of three distinct aspects. The first aspect is the psychological world of the individuals involved in organizational buying decisions. The second aspect relates to the conditions that precipitate joint decisions among these individuals. The final aspect is the process of joint decision making with the inevitable conflict among the decision makers and its resolution by resorting to a variety of tactics" (pp. 52). Much of the industrial marketing literature is devoted to the second two aspects of Sheth's framework (e.g., Choffray & Lilien, 1980; Morris, Berthon, & Pitt, 1999; Pettigrew, 1975). While multivariate techniques have occasionally been used to enlighten such contexts (e.g., Lockett & Naudé, 1991), it is an understanding of the first of Sheth's aspects (i.e., "the psychological world of the individuals involved in organisational buying decisions,") which can be enhanced by the statistical tool kit discussed in this article. The introduction of such tools into the industrial marketing literature may encourage a new stream of research into the process of individual decision making within the firm—an area that has been somewhat neglected, perhaps for want of suitable techniques.

Another model, which may aid managerial decisions as to the appropriate contexts for using statistical techniques, is the buygrid model developed by Robinson, Faris, and Wind (1967). They argue that organisational buyer behaviour varies according to the buying situation, which may be classed as "new task," "modified rebuy," or "straight rebuy". It is more likely that decision making at the new task stage will encompass Sheth's joint decision making and conflict resolution contexts as more risk is involved, while the straight rebuy stage is most likely to comprise individual decision making. Most buying tasks fall into this latter category, but more effort is expended on understanding the more complex intricacies of coalition decision making on new and therefore more highly involving purchase situations. Yet, if an understanding of the minutiae of the decision process of individuals making seemingly routine purchases can be enhanced using statistical techniques, then this offers potentially large competitive advantages for industrial marketers.

4. The tool kit

We now present details of the three multivariate techniques, which we believe can help organisations understand the behaviour of individual buyers within customer firms.

4.1. Conjoint analysis—strategic level tool

Conjoint analysis uses the idea that when confronted with a choice between suppliers and brands, buyers "must make an overall judgement about the relative value of those [supplier/brand] characteristics or attributes; in short, he must order them according to some criterion" (Green & Wind, 1975). Conjoint analysis allows researchers to explore the buyer's process of evaluation and trade-off and to determine their perceptions of the relative importance of the various attributes (Webster & Wind, 1972; Wittink & Cattin, 1989). Chisnall (1997) notes, "when people buy products and services, they tend to compare alternative suppliers and make some evaluation (which will vary in depth according to the nature of the purchase) of the advantages and disadvantages, which they perceive as attached to certain sources of supply and/or brands" (pp. 393–394), and goes on then to suggest that conjoint analysis is frequently the most appropriate technique by which researchers can understand buyer behaviour associated with this process. Moreover, and importantly for B2B contexts, the extraordinary number of applications of conjoint analysis (see Cattin & Wittink, 1982; Wittink & Cattin, 1989) is in part due to the fact that, unlike most statistical procedures applied in typical B2C research methodologies, a large sample size is not needed to draw meaningful results.

From a strategic standpoint, understanding this compensatory decision-making behaviour can be used by marketing managers in several very fundamental ways: to gauge price sensitivity, to inform product development, or to develop marketing campaigns that focus on those attributes which buyers value most highly (Malhotra & Birks, 2003). For example, Auty (1995) reports on the use of conjoint analysis in different industrial environments, describing how it was used to develop marketing campaigns/product positioning for a product in the IT industry in one instance, and a second example of using the approach to price a product in a commodity market characterised by a limited number of buyers. Details of other applications can be found in Cattin and Wittink (1982), Wittink and Cattin (1989), and Wittink, Vriens, and Burhenne (1994).

As powerful as the technique is, managers need to be aware of the dangers inherent in using this approach in developing their understanding of any marketplace. While an obvious advantage is that the approach is sample size independent in that it can be used with a single respondent, this is also clearly a disadvantage in that the danger exists that too few respondents are used; hence, the full variance in the requirements of the marketplace are not fully understood. In addition, great attention needs to be placed to the research design: if the attributes chosen, or the levels at which they are evaluated, are not the most salient to the buyers, results will be impaired. Finally, it is not possible to extrapolate the importance of attribute levels not specifically tested. While the practical relevance of many of these issues will emerge in our following example, more information can be gleaned from practitioner-oriented sites such as http://www.sawtoothsoftware.com.

4.2. Cluster analysis—operational level tool

The second approach in our suggested tool kit is cluster analysis. After conjoint analysis has revealed the relative importance of the various levels of the product or service attributes, cluster analysis can be used to identify sets of respondents who value the various attributes and alternatives in a similar way. Simply put, cluster analysis groups together those respondents that are in some sense similar in their preferences. There are a range of different metrics that can be used to assess the degrees of closeness, which need not be discussed here (see, e.g., Everitt, 1993), but the principal output of the various routines available is the dendrogram, which we examine in more detail in our discussion of the application example of the techniques below.

Cluster analysis has direct benefits at the operational level, with managers being able to determine more precisely what offerings it is that the different segments require and hence how to allocate financial and other resources. For example, Birks and Birts (1998) report on how the technique has been used to categorise the behaviour of European managers in terms of their changing approaches to cash management. The managers were clustered in 20 different segments, each of which was relatively homogeneous with respect to their future plans. This allowed firms focusing on this market to allocate resources differentially, according to whether the segment was focused on restructuring through new electronic systems, quality, the status quo, etc.

As with conjoint analysis, the user must be aware of some limitations to the technique. Cluster analysis is a complex tool, and many decisions that ultimately affect the quality of the solution are reliant on analysts' judgements rather than statistical inference (Malhotra & Birks, 2003). In particular, determining the appropriate number of clusters is both difficult and subjective (Aldenderfer & Blashfield, 1984).

Determining reliability and validity of the cluster solution can also be problematic. Reliability can be assessed by repeating the analysis using *different* methods or measures of similarity on the *same* data set or alternatively using the *same* methods/measures on a *different* data set (a holdout sample) and determining the degree of consistency between solutions. A "split-half" analysis is essentially a hybrid approach, using the *same* method/measures on the *same* data set that is conventionally divided into two halves that are analysed separately and solutions are compared (Hair, Anderson, Tatham, & Black, 1992). Use of holdout samples can be particularly problematic in B2B applications because sample sizes are generally small (Ketchen & Shook, 1996).

Criterion validity concerns establishing a cluster solution's usefulness for predicting other important outcomes. Ketchen and Shook (1996) found in their review of the application of cluster analysis in the strategic management literature that 54% of strategic management studies failed to assess this, while 24% of studies erroneously tested it by demonstrating that clusters differed across the variables used to construct them. Users of cluster analysis should, instead, assess whether clusters differ across external variables (once not used to generate them) that are theoretically related to them (Everitt, 1993; Hair et al., 1992).

4.3. Correspondence analysis—tactical level tool

The third tool is correspondence analysis, a perceptual mapping procedure (see, for example, Greenacre, 1984; Hoffman & Franke, 1986). This is an approach ideally suited to exploring any 2×2 matrix of data in search of additional insights. The approach is based on a variant of principal components analysis, and seeks to capture the complex multidimensionality of the data in a lower number of dimensions. The output is typically in the form of perceptual maps, where the rows and columns are depicted as points. While multiple maps may be produced using various dimensions, managerial efficacy is usually best rewarded by focusing on the first two dimensions, those which capture the majority of the underlying variance. When used in conjunction with cluster analysis, the input matrix consists of rows (the respondents) and columns (their rankings of the different product/attribute combinations). Two aspects of how to interpret the output need to be highlighted. First, those respondents (or attribute combinations) that are in some average sense "similar" across the different combinations (or respondents), will be plotted relatively closely together. Secondly, those respondents (or attribute combinations) that are average or nondiscriminatory in their scores across the various attribute combinations (or respondents) will be plotted close to the intersection of the axes. We will return to these points when we examine the application of the techniques below.

On a tactical level, because the output is a map, it provides a very clear visual representation of the difference in priorities between different customer groups. This can be used as a simple but effective aid in briefing the sales force or circulating marketing information in digestible form throughout the organisation. Examples of this type of application can be found in Naudé, Lockett, and Gisbourne (1993), where the perceptual maps were used to guide the thinking of a sales force in the chemical industry as to how their company and the competitors were viewed according to several attributes. A second example (Hipkin & Naudé, 1999), also in the chemical industry, shows how markets can be segmented according to the underlying importance of a range of attributes.

While the use of perceptual maps is generally seen as a positive contribution to the manager's tool kit, they too are not without their disadvantages. The most important of these, and one that is often not fully appreciated, is that the two dimensions of the perceptual map may not account for a significant amount of the variance in the data and that users need in fact to think of the data in more than just two dimensions. This problem will reemerge below, where we discuss a practical application of the tool.

Having made a case for the consideration of three particular multivariate techniques to be used in B2B contexts to enable a better understanding of the individual decision-making processes of industrial buyers, we now illustrate the use of these tools.

5. An application of the tool kit

5.1. Background to the study

The study reported here was sponsored by a UK supplier of life science research chemicals (LSRC) who hoped that the use of the tool kit would provide an enhanced understanding of the process undergone by their clients in selecting a supplier. Across the range of life science disciplines (which includes pharmacology, physiology, neuroscience, biochemistry, and cell biology), scientific researchers frequently have a need to elicit, modify, or suppress the action of various biological systems. One of the most common ways in which this can be achieved is through the use of "drug-like" chemicals that interact with biological systems and produce a particular biological effect or response. In addition to "pure" academic studies, research using LSRC frequently forms the basis of pharmaceutical companies' drug discovery programmes. Thus, LSRC buyers fall into two major groups: university academics and researchers inside large pharmaceutical companies. The decision makers are thus expert individuals. At the time of the study, the supplier selection process in both groups was poorly understood within the industry, and little or no research had been published in this area.

The study reported here was undertaken to identify the range and relative importance of the variables that affect the decision to select a supplier of LSRC, a product that is available from several competing suppliers.

5.2. Conjoint analysis procedure and results—a strategic tool

The conjoint analysis was carried out in six stages as is the norm (Malhotra & Birks, 2003). The first of these was to "identity the attributes and attribute levels to be used in constructing the stimuli" (ibid., pp. 634). This process was based on an analysis of the available secondary data and the results of initial qualitative research (Cattin & Wittink, 1982). Unsurprisingly, the process identified a large number of potentially applicable attributes, more than could reasonably be accommodated in a useable orthogonal design. Based on qualitative research and a managerial actionability criterion, five attributes were selected: geographic location of the supplier (management can affect this by choosing to open, maintain, or close UK sites), quality of technical support (management can devote more or less of their resources to this issue), frequency of citation in journals (management can seek to increase this by providing samples to key researchers, for example), quality of a supplier's catalogue and technical literature (something over which management has direct control), and extent to which a supplier manufactured the products in its range "in-house" (as this has implications for make or buy decisions; Ford et al., 1999). Each attribute was assigned three levels.

The second stage of the conjoint procedure was to construct the stimuli for presentation to respondents. Two methods of stimulus presentation are commonly used: two-factor evaluation or full profile (also known as multiple factor evaluation; Malhotra & Birks, 2003). In the two-factor evaluation, respondents are asked to evaluate pairs of alternatives (such as lemon scent and recyclable packaging), while in the full profile method, a set of full or complete profiles representing different levels of all of the attributes being studied, effectively "mini descriptions" of a range of possible suppliers or brands, are presented to respondents for evaluation. Evidence in the literature suggests that the full profile method is the most widely used, as it is believed to more closely replicate the actual buying situation (Wittink & Cattin, 1989). In this study, the nature of the research question lends itself to the full profile method; accordingly, this was the approach adopted.

The third stage of a typical conjoint analysis requires the researcher to decide on the input form of the data. Arguably the most popular method used is to ask respondents to rank (as opposed to rate) the various profiles in order of preference. As Malhotra and Birks (2003) note, "proponents of ranking data believe that such data accurately reflect the behaviour of consumers in the marketplace" (pp. 637). This being the case and given that this approach has been used successfully in several studies based on the full profile methodology (Auty, 1995; Naudé & Buttle, 2000), the decision was taken to use ranking as the preferred method of data input.

The company in the study operates around 500 accounts with 200 organisations. Questionnaires were sent to 500 named individuals selected randomly from the database and a 14% response level was achieved. Some of the questionnaires were unusable leaving a final response of 8.8%. The proportion of industry and university respondents (11.4% and 88.6%, respectively) reflects *reasonably* closely those in the original sample of 500 (20.8% and 70.6%, respectively), suggesting that the replies received represent a usable, "reliable," and "valid" sample of the overall population of $\sim$ 4000. Furthermore, no usable replies were received from the 43 respondents of unknown affiliation. This is perhaps unsurprising, however, as an examination of their addresses reveals that in most cases they are either clinicians (and LSRC are unsuitable for clinical use) or private individuals and one might reasonably infer therefore that they are the least likely members of the sample tested to use LSRC and accordingly the least likely to return usable questionnaires.

Of the 28 unusable responses, 9 were returned stating that the individual to whom the questionnaire had been addressed had left, 9 were returned having not been completed but with comments from the recipient that they had changed role within their organisation and were no longer involved with LSRC, 4 were received extremely late, 5 were invalid (e.g., the respondents had scored rather than ranked the alternative suppliers), and 1 was simply returned completely blank. Forty-four data sets were therefore used. While this response rate may seem to be low, it does in fact reflect industrial norms. Malhotra and Birks (2003), for example, suggest that a response of about 15% can be expected when there is no premailing or postmailing of respondents.

The remaining stages (Stages 4–6) of the conjoint experiment relate to data analysis, and as Wittink and Cattin (1989) note, increasingly, these are carried out using some appropriate software package. This was the approach taken in this case, the data being analysed using SPSS and considered in terms of *utilities* and *importance* (as is normal in conjoint analyses). The *utility* (or part worth) of an attribute is an indication of a respondent's preference for that particular attribute level. For example, an experiment may explore the importance of a supplier's location and find that for a given population a supplier in the UK represents a utility of 1.06, a supplier in Spain a utility of -0.24, and a supplier in Japan a utility of -0.82. This would indicate that the respondents have a strong preference in favour of UK suppliers (as 1.06>0) in preference to those in Spain or Japan, which the respondents would view as being more or less equally (un)attractive (as they have utilities of <0). Table 1 shows the results of the conjoint analysis.

We see from Table 1 that the quality of a supplier's catalogue and promotional literature is the most important attribute of the five tested, having a mean importance of

Table 1
Overall conjoint analysis results

Attribute	Level	Utility	Importance (averaged)
Proportion of supplier's product range that the supplier manufactures	None (0%)	− 0.32	10.30
	Half (50%)	− 0.14	
	All (100%)	0.46	
Supplier's closest sales location to the UK	Outside UK/Europe	− 0.91	14.15
	Europe (not UK)	− 0.17	
	UK	1.08	
Quality of supplier's catalogue and literature	Poor	− 2.60	28.90
	Average	0.14	
	Good	2.46	
Frequency with which supplier is cited in the literature	Never	− 2.08	22.73
	Occasional	0.42	
	Frequent	1.66	
Quality of supplier's technical support	Poor	− 2.30	23.92
	Average	0.22	
	Good	2.08	

28.90. Catalogues and literature that are regarded as being "good" or "average" have positive utilities; therefore, suppliers that are perceived to be poor in this regard are unlikely to be viewed favourably by these respondents. We can see from Table 1 that the best offering that can be constructed is the one that maximises the utility score on each attribute: manufacturing the full range of products (0.46), being based in the UK (1.08), having good quality promotional material (2.46), being frequently cited (1.66), and having good technical support (2.08) results in an overall utility of 7.74. We can immediately see the importance of the catalogue and literature quality, in that an offering that is poor on this attribute can only achieve a maximum overall utility of 2.68 [i.e., $0.46+1.08+(-2.60)+1.66+2.08$].

In contrast, the proportion of their product range that suppliers manufacture themselves is the least important of the attributes, with a mean score of 10.30. The quality of a supplier's technical support, the country in which the supplier is located, and the frequency with which a supplier is cited in the life science literature are of intermediate importance. As shown in Table 1, suppliers in the UK are viewed favourably as are suppliers that provide good or average quality technical support.

5.3. Cluster analysis procedure and results—an operational tool

Having examined the relative importance of the five attributes and the utility of each of the 15 alternatives, the next stage of the analysis was to carry out a cluster analysis with the aim of identifying sets of respondents who value the various attributes and alternatives in a similar way. SPSS software was used to perform the analysis, with the results shown in Fig. 1.

As noted by Malhotra and Birks (2003), there are no hard and fast rules that can be used to objectively determine the number of clusters that should be identified, but looking at the dendrogram in Fig. 2, five clusters "suggested themselves," each of which is shown bordered by a dotted line. Of these, three clusters accounted for 37 (84%) of the respondents, the largest cluster containing 18 respondents (30 through to 44 in the diagram). Of the remaining two clusters, the smallest contained only 2 respondents (32 and 13). This finding implies that the customer base is not homogeneous but that there may be up to five groups of customers differentiated by their decision-making criteria. This has operational implications in that the way each of these groups should be approached must be differentiated. The next stage is to identify the characteristics of the clusters. This can be performed by examining the raw cluster data. However, for B2B practitioners unfamiliar with data analysis, it is probably more appealing to examine the data in two-dimensional space. This was the approach adopted in this study and the data were analysed using correspondence analysis (Greenacre, 1984).

5.4. Correspondence analysis procedure and results—a tactical tool

The output of the correspondence analysis is shown in Fig. 2. It is important that this is interpreted with the output of the dendrogram in Fig. 1 in mind. The perceptual maps resulting from correspondence analysis can only be represented in two dimensions and thus are, to some extent, an oversimplification of the data. In this case, the two primary dimensions shown in Fig. 2 account for 47.7% of the variation in the data. Although a figure of 47.7% is sufficiently high to be useful, it also serves to highlight the fact that there are several other significant dimensions to the data: two points that appear close in these two dimensions might well be further apart on a third, vertical dimension. This is particularly the case with respondents such as 43 in Cluster 4 (Clus4), 29 in Cluster 2 (Clus2), and 13 and 32 which together form Cluster 5 (Clus5): their group membership is more readily interpreted from the dendrogram in Fig. 1. In spite of this disadvantage, the advantage of combining the two approaches is that the correspondence analysis yields insight into what it is that each cluster or segment is most associated with, an insight that cannot be gleaned from Fig. 1.

The perceptual map provided a wide variety of useful insights into the data set and proved to be easily interpretable by a range of managers in the organisation. Firstly, it shows that the Cluster 1 (Clus1) consisting of five respondents, 18 to 4 (from Fig. 2), is significantly different from the others. Notably, it includes only respondents from universities and is particularly associated with alternatives E, J, and N, which represent alternatives in which the quality of a supplier's catalogue and literature, the frequency with which they are cited in relevant journals, and the quality of their technical support are all at the highest level. In contrast, the

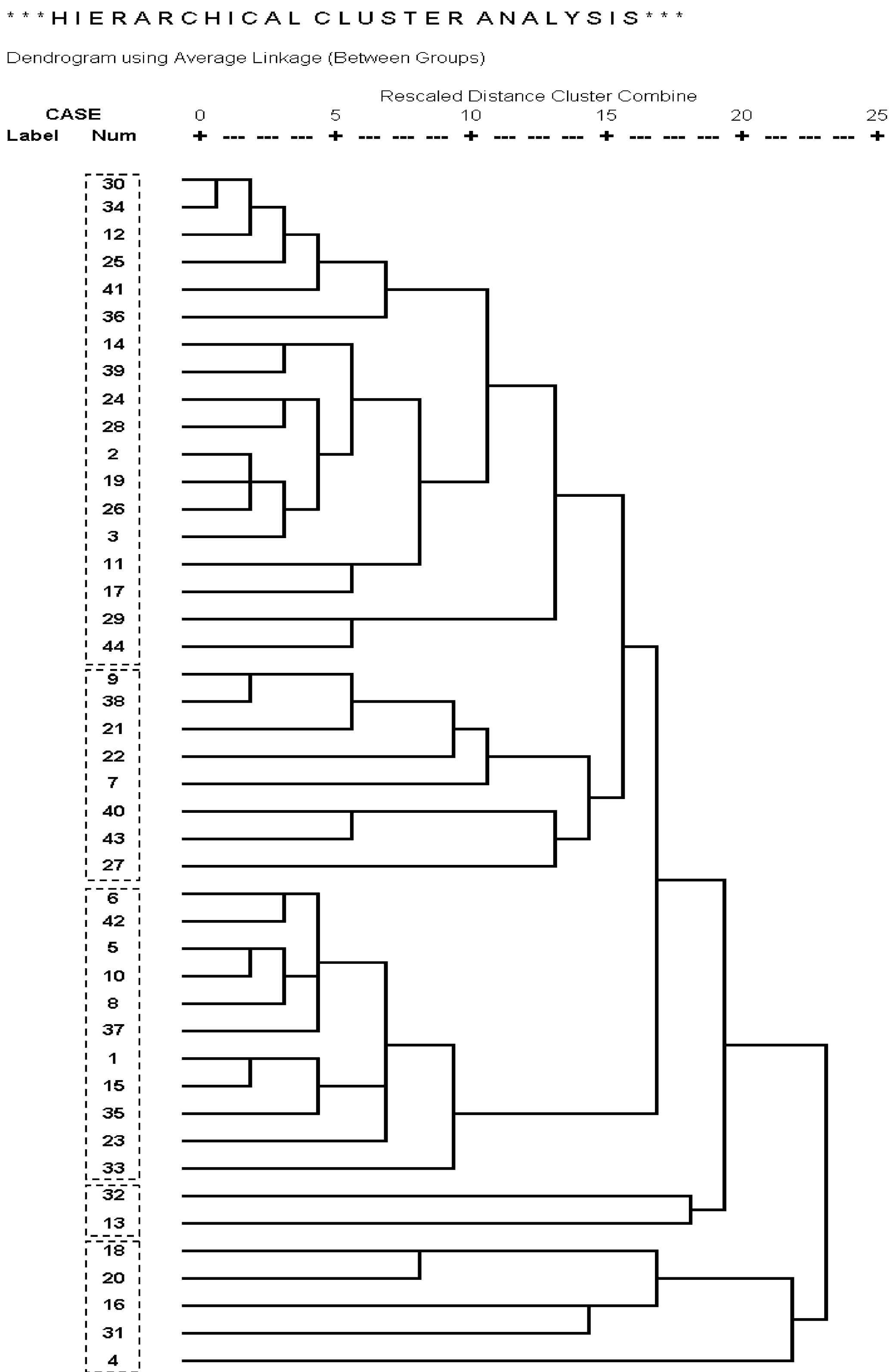

Fig. 1. Results of the cluster analysis.

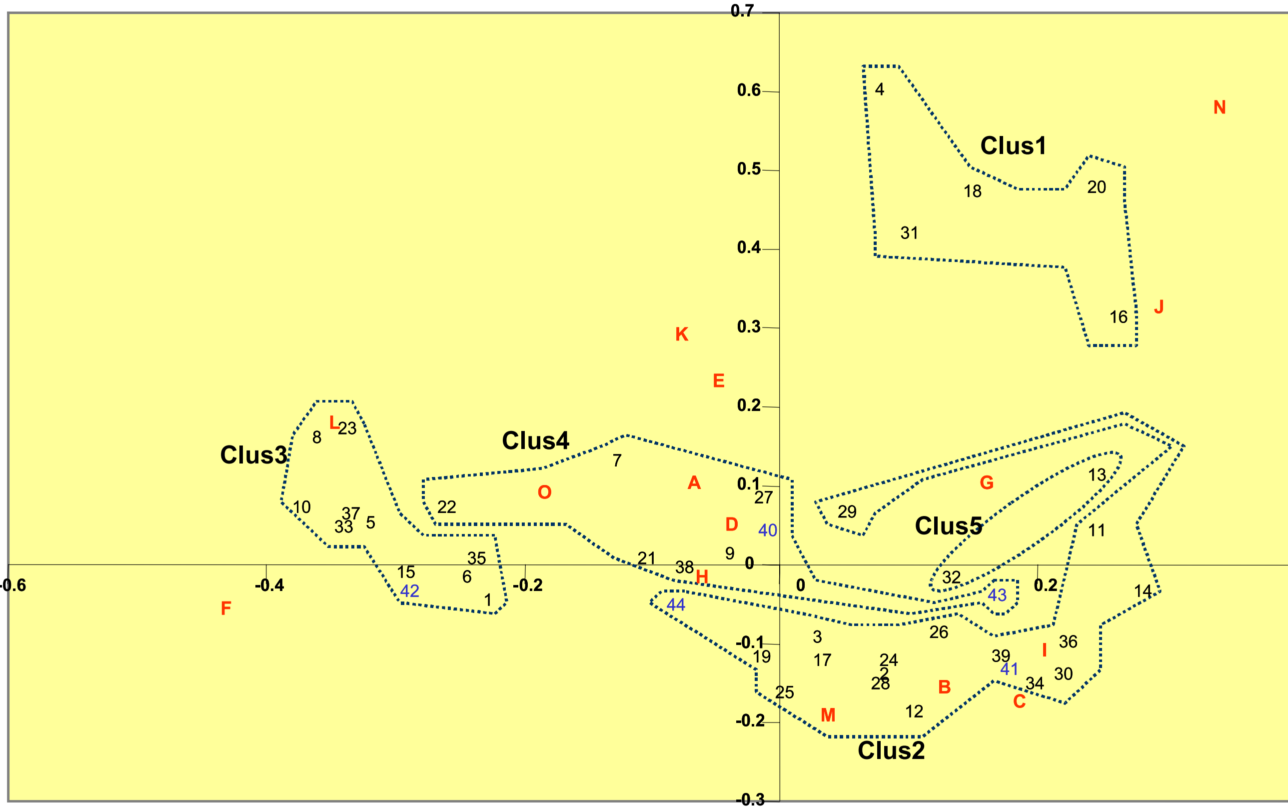

Fig. 2. The results of correspondence analysis.

members of this cluster appear relatively unconcerned with a supplier's location or the proportion of its product range that is manufactured in-house. This being the case, the cluster was labelled "information seekers" and accounted for 11.4% of the (valid) respondents.

Of the remaining clusters, the most heavily populated is Clus2 consisting of respondents 30 through to 44, which accounts for 40.9% of the respondents. It is interesting to note, however, that respondent 29 is something of an outlier on these two dimensions, being almost as close to the members of Clus4 as it is to its own. This is a reflection of the fact that the two axes only account for 47.7% of the variance in the data; therefore, factors that might more closely associate respondent 29 with the rest of its cluster may not have been taken into consideration. Overall, Clus2 is closest to alternatives B, C, I, and M, which represent hypothetical suppliers characterised by being frequently cited in journals (i.e., suppliers that have been "tried and tested" by others). Accordingly, in contrast to attributes, such as a supplier's location or the quality of their catalogue and literature, which were seen as relatively unimportant, the cluster was labelled "tried and tested".

The next most heavily populated cluster is Cluster 3 (Clus3), accounting for 25.0% of the respondents and consisting of respondents 6 through to 33. It is close to alternatives F and L, suggesting that the members have a strong preference for suppliers in the UK and are relatively unconcerned with attributes such as the frequency with which a supplier is cited in a journal as having supplied the LSRC used. As a result, this cluster was labelled "anglophiles".

The last large cluster (Clus4) consists of respondents 9 through to 27 and is close to alternatives A, D, H, and O. Accounting for 18.2% of the respondents, they are characterised by a preference for suppliers that are located *outside* the UK and who manufacture at least half of their product range themselves. This cluster was labelled "offshore producers". Notably, respondent 43 is something of an outlier, being closer to Clus5, the likely reasons for this are the same as for respondent 29.

Finally, Clus5 consists of just two respondents (4.5% of the total), both from universities. It is characterised by its close proximity to alternative G, which suggests that the members of this cluster favour UK suppliers that are frequently cited in journals and are relatively unconcerned with the quality of a supplier's technical support. Overall, this suggests that the members of this cluster do not feel the need to rely on a supplier for technical support but to seek reassurance that suppliers have been "tried and tested" by other scientists. Accordingly, the cluster was labelled "cautious academics".

These cluster labels were then attached to the cluster positions on the original correspondence analysis output (Fig. 3) so that an easily digestible diagram could be

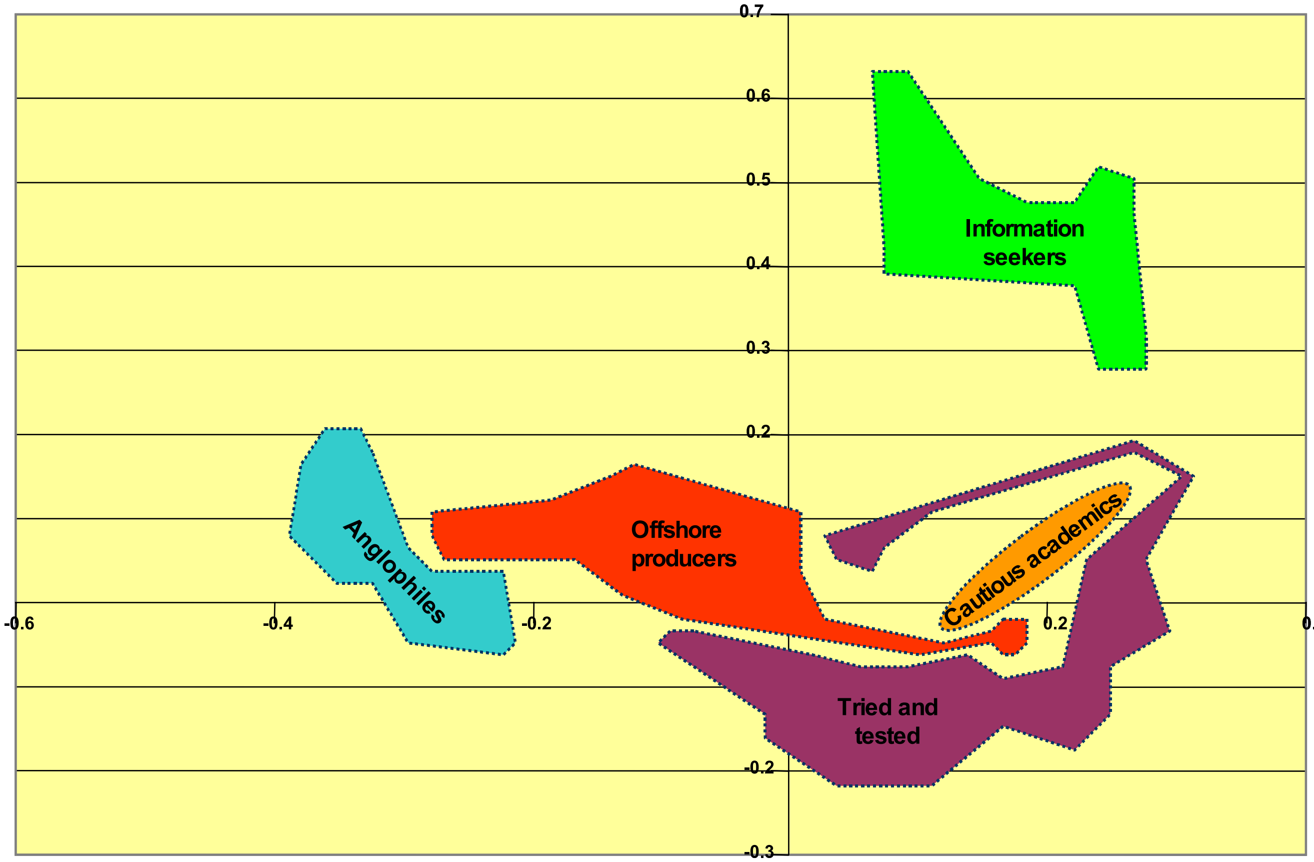

Fig. 3. Naming the clusters.

disseminated throughout the organisation to explain the existence of differing customer segments.

6. Discussion

The company sponsoring the study found the use of a multivariate statistical tool kit highly illuminating on the strategic, operational, and tactical levels and has already taken several practical actions.

On a strategic level, the conjoint analysis has helped the company to develop marketing campaigns that focus on those attributes that buyers value most highly (i.e., the quality of catalogues and promotional literature). Since the study, the company has upgraded the quality of the catalogue (the most important attribute) in terms of layout and quantity and type of information. Quarterly mailings, which include extracts from the brochure, have also been enhanced as have posters, exhibition flyers, advertisements, trade show booths, and the Web site. Given the relatively high importance of technical support, the research was also used to support a move to increase the resources devoted to technical support (in addition to the changes made to the Web site). Additional front-line technical support personnel are being recruited to improve the response times to technical inquiries.

On an operational level, the results of the cluster analysis were used to inform a debate in the company on whether the company should represent itself as a British company worldwide, as a British company in Europe, as a U.S. company in the United States, or simply as an "international" organisation. This was particularly important as current marketing resources do not allow for local versions of all literature to be produced. The ultimate decision taken, informed by the research, was that where generic literature was used, they should aim for a "mid-Atlantic" image defaulting to UK where a decision had to be made (e.g., UK-sized A4 paper, UK spellings, etc.). The hope was that this would not alienate or confuse either the offshore producers or the anglophiles.

Given the combined size of the information seekers, tried and tested, and cautious academics clusters, the practice of giving free samples to prospects in the hope of generating papers and articles, which in turn will attract more of these conservative individuals, has been resourced and extended.

The research has also highlighted the need for the company to improve its segmentation strategy. Previously, customers and prospects were simply categorised according to the product type they used (e.g., cannabinoids) as opposed to being segmented according to their needs/behaviours. Poststudy, the mailing list is being reexamined to ensure that customers are segmented in terms of their needs and characteristics.

On a tactical level, key personnel within the organisation are now aware of the clusters that were identified in the study. Within the marketing department, the needs of the information seeker, tried and tested, and cautious academics, in particular, have been understood and acted on. This is particularly useful given that, in addition to developing the direct mail campaigns, the marketing team also acts as a sales force, manning the booth at international conference and exhibitions.

7. Conclusions and recommendations

This article began by arguing that the assumption of fundamental difference between B2B and B2C marketing may not always be of practical benefit to marketing managers. Specifically, it was argued that an unwillingness to see the relevance of B2C techniques to the analysis of B2B issues has resulted in little use by B2B marketers of the sophisticated multivariate statistical techniques used to understand the decision-making behaviour of individual consumers. It was argued that the differences between the two marketing contexts are constituted by degree rather than form and that where the focus of interest is individual decision making rather than the process of joint decision making or decision conflict; then, multivariate statistical techniques are likely to be useful. It was further suggested that this focus is likely to be most predominant in straight rebuy contexts. This article has gone on to show how three techniques can be used together in a tool kit to inform marketing strategy, operations, and tactics. Finally, a study in the life sciences industry has demonstrated on a practical level how these tools can be applied and what tangible outcomes can result.

This study has added to, and opened up, several research streams. Firstly, it has made a contribution to the literature on the use of multivariate statistics in industrial marketing and has broadened the possibilities of such applications. Secondly, it has addressed a specific situation in which B2C concepts can work in a B2B context and opens the way to the development of a diagnostic framework to enable B2B managers to more easily identify contexts in which B2C tools can be used effectively. Thirdly, it has added to the growing literature that advocates seeking similarities rather than differences between B2B and B2C marketing.

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