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Carlos M.F. Monteiro, Sally Dibb, Luis Tadeu Almeida

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Carlos M. F. Monteiro

CEG-IST, Centro de Estudos em Gestão, Instituto Superior Técnico,

 Universidade Técnica de Lisboa

Av. Rovisco Pais, 1049-001 Lisboa, Portugal

E-mail: carlos.monteiro@ist.utl.pt; Tel: +351 218417981; Fax: +351 218417979

Sally Dibb

Open University Business School, Open University,

Milton Keynes, MK7 6AA

United Kingdom

E-mail: S.Dibb@open.ac.uk;Tel: +44 1908 652787

Luis Tadeu Almeida

CEG-IST, Centro de Estudos em Gestão, Instituto Superior Técnico,

 Universidade Técnica de Lisboa

Av. Rovisco Pais, 1049-001 Lisboa, Portugal

E-mail: luis.tadeu@fordesi.pt;Tel: +351 218417981

Abstract

This article explores the use of multivariate techniques to build perceptual maps that show the perceived competitive positions of a set of ethical drugs. The data were drawn from a commercial panel of 283 family doctors working for the UK National Health Service. Factor analysis was applied to identify the main dimensions used by doctors to perceive and evaluate antihypertensive brands. Perceptual maps showing the competitive positions of 14 antihypertensives were produced using the factor scores of the medicines. Multiple regression analysis enabled the relative importance of each perceptual dimension to be determined. The results reveal that doctors use a small number of perceptual dimensions to evaluate competitive antihypertensive drugs, namely: "medical support", "long term efficacy", and the "additional beneficial effects" provided by the brand. The implications for marketing managers in the ethical

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pharmaceutical industry are explained and ways in which the perceptual analysis can be used to guide strategic marketing decisions considered.

1. Introduction

Understanding how buyers perceive competitive offerings is paramount in the development of competitive marketing strategies, not only for consumer and industrial offerings (e.g, Kotler and Keller, 2006; Dibb *et al.* 2005, Hooley *et al.*, 2004) but also for ethical pharmaceutical products or prescription drugs (Vanderveer and Pines, 2007; Lidstone and MacLennan, 1999; Smarta, 1996; Corstjens, 1991). Perceptual mapping, an important analytical tool in marketing research, is commonly used to investigate the perceptions of buyers (Green *et al.*, 2003, 1988; Neal, 1988; Hauser and Koppelman, 1979) and can also support the development of marketing strategies. However, the multivariate statistical techniques for building perceptual maps used in consumer and industrial markets have not yet spread through the ethical pharmaceutical industry. This research aims to extend literature on perceptual mapping by using factor analysis to produce perceptual maps that reveal the perceived competitive positions of prescription drugs.

The paper is organised as follows. Firstly, a literature review on perceptual mapping and its support for strategic marketing decisions is presented. Secondly, details of the data and the empirical study are shown. Thirdly, factor analysis is used to determine the main perceptual dimensions doctors use to evaluate the competitive antihypertensive drugs analysed. Fourthly, the perceptual maps are built. These use the ethical drugs' factor scores and the results of cluster analysis to display the perceived competitive positions of ethical pharmaceutical products and product classes in the sample. Fifthly, the relative importance of the main evaluative dimensions is determined with multiple regression analysis. Ways in which the applied methodology can be used to improve the competitive position of ethical brands are then considered. Finally, the study's conclusions are presented and further research directions proposed.

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2. Supporting Strategic Marketing Decisions with Perceptual Maps

According to Shocker (1987), the aim of perceptual mapping is to model how a market sees a set of competing products "in some memory-like or cognitive sense". Perceptual mapping techniques are able to represent the competitive structure of markets "in a (visual) manner that facilitates differentiation and positioning decisions" (Lilien and Rangaswamy, 2003). As people process pictures faster than text (Paivio *et al.*, 1968), it is easier to see and interpret relationships when they are presented graphically than in tables with numbers (Cahill, 1995). Perceptual mapping methods capture customers' perceptions of competitive offers, which are then displayed in perceptual maps with few strategic dimensions. Each axis represents a key dimension used by customers to perceive and judge competitive offers. Perceptual mapping is frequently used to position or reposition an offer, to measure the success of positioning or repositioning exercises, or to monitor the evolution of the positioning of competitive brands over time (Neal, 1980). It can uncover unfulfilled gaps in the market, the perceived relative strengths and weaknesses of competitive products, the intensity of rivalry between specific competitive offers, and opportunities for gaining a differentiated position. Moreover, "its powerful graphic simplicity appeals to senior management and can stimulate discussion and strategic thinking at all levels of all types of organizations" (Wittenschlaeger and Fiedler, 1997). Together these qualities have made perceptual mapping a valuable strategic management tool.

Analytical methods for developing perceptual maps can be categorised into compositional and decompositional approaches (Green *et al.*, 1988). Compositional methods assume that consumers can decompose their perceptions of brands into separate attributes and can evaluate each brand according to these attributes. Brand perceptions based on these attributes are first gathered with direct measures; a multivariate technique is then used to reduce the original number of product attributes to a small number of strategic dimensions, and the competitive offerings are plotted using their scores along these new dimensions. Multivariate techniques generally used with compositional approaches are factor analysis, discriminant analysis and, when the input is nominal data, correspondence analysis (Johnson, 1999; Neal, 1988).

Decompositional methods assume that people have global perceptions of objects which cannot be decomposed. This requires a perceptual map based on overall comparisons between competitive offerings, so that the researcher does not specify an attribute set. The aim is to identify the relative positions of the products based on customers' judgements of the similarity/dissimilarity of competitive offers. Decompositional approaches use a variety of nonmetric multidimensional scaling methods, for example KYST (Kruskal, 1964a and 1964b). Compositional methods have been found to be superior to decompositional methods in terms of theory, interpretability of the dimensions, ease of use, and predictive validity (Hauser and Koppelman, 1979). However, Shocker (1987) argues that these two classes of methods should be viewed as complements rather than as substitutes. This is because compositional methods place "a great burden on the researcher to correctly develop a set of attributes and ways of scaling products on those attributes before the analysis begins", whereas decompositional methods "by allowing the consumer to impose his/her own structure … may even suggest attributes of products that might otherwise not have come to mind".

Perceptual maps can capture the preferences (the most valued region of the perceptual space) as well as the perceptions of respondents, thus showing which products/brands are most attractive. The ideal point model assumes that respondents prefer a point in the perceptual space corresponding to their ideal product/brand. Isopreference curves, where products/brands lying on the same curve have equal preferences, are developed taking the ideal point as the centre. The most preferred products/brands are those positioned on the isopreference curves closest to centre (Van Deun *et al*., 2005). By contrast, the vector model, which assumes that respondents have a preferred direction in the perceptual space, calls for the identification of an ideal vector along which a product/brand should be moved to maximise customer preference; products/brands equally preferred are those positioned on the same perpendicular to the ideal vector (Urban and Hauser, 1993; Shocker, 1987).

According to Myers (1992), perceptual mapping has its origins in the work of Hotelling (1929), an economist who began developing techniques for positioning objects in virtual spaces long before psychologists in the 1950s. The use of perceptual mapping techniques has been widespread in quantitative marketing research since the 1960s, with the importance of perceptual mapping methodologies in marketing research likely to

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continue (Green *et al.*, 2003). Numerous studies have produced perceptual maps for objects as diverse as countries, new product concepts, beer brands, cities, automobiles, psychology journals, movie critics, cereal brands, human genes, areas of economic activity, food products and diet concepts, breath freshener products, and financial services (see for example, Lattin *et al.* (2003) and Shocker (1987)). Even perceptual maps for brands of king size cigarettes have been developed (Hooley, 1984).

Recent studies have considered the production of perceptual maps for the brand image of deodorants (Torres and Bijmolt, 2009), travel agencies (Kim D. *et al.*, 2007), political candidates (Kamakura and Mazzon, 2007), restaurants (Natasa *et al.*, 2007), top journals from various academic business disciplines (Biehl *et al.*, 2006), leather products (Faye *et al.*, 2006), print advertisements of automobiles (Hartmann *et al.*, 2005), tourism destinations (Kim S. *et al.*, 2005), development of cities (Festervand, 2004), casinos (Kim W. *et al.* 2004), image of destinations (Kozak *et al.*, 2003), and states of USA (Chen and Uysal, 2002). Multidimensional scaling methodologies are the most widely used, followed by correspondence analysis and factor analysis.

However, there are very few published studies using quantitative perceptual maps to support competitive marketing strategies in the ethical pharmaceutical industry. Only three studies using multivariate perceptual mapping techniques have been published in this area. The study by Neidell (1969) used nonmetric multidimensional scaling techniques to produce perceptual maps for six competing ethical drugs, including one ideal brand, from two therapeutic classes of medicines, namely the ataractics (tranquilizers) and anorectics (anti-obesity drugs). The second study used correspondence analysis to develop perceptual maps showing the perceived positions of six competitive medicines belonging to the ethical analgesics market; these maps were used to guide the repositioning of an ethical drug (Hurrell *et al.*, 1997). The third study, which actually analyses preference rather than perceptual data, used a spatial gravity multidimensional scaling methodology to derive a two dimensional joint space showing seven prescription brands, from an unrevealed market, and the physicians' ideal points (DeSarbo *et al.*, 2002).

Surprisingly, although factor analysis has been widely used to identify consumer choice dimensions and to display the perceptual positions of competitive offers (Neal, 1988;

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Shocker, 1987), it has never been applied in the ethical pharmaceutical industry or in related areas such as over-the-counter, dental or veterinary medicine. This research is the first to apply factor analysis[1], a compositional approach, to produce perceptual maps that reveal the perceived competitive positions and the key drug choice dimensions of a set of ethical pharmaceutical brands. This study uses fourteen ethical drugs, which is a much larger number in comparison with those used in previous studies. For some very competitive ethical markets pharmaceutical managers might benefit from having perceptual competitive information on a large set of drugs. In addition, this is the first time that multivariate perceptual mapping techniques have been used to research the antihypertensives market. The vector model is used to capture the relative importance of the choice dimensions, therefore assuming that doctors use dimensions where "more (or less) is better". This methodology should improve the knowledge of how doctors choose the drugs they prescribe and support marketing managers in developing better strategies and practices to match the needs of target doctors.

3. Data and Empirical Study

This research examines the antihypertensive drugs market. Antihypertensive medicines are used to control high blood pressure (hypertension), a disease affecting around one billion people worldwide (Kearney *et al*., 2005; JNC 7 report, 2004). Various categories of drugs are used to treat hypertension, each lowering blood pressure through a different mechanism[2]. Although the treatment of hypertension varies from country to country (Fretheim and Oxman, 2005), any drug from each category can be used as first line therapy in the treatment of mild hypertension (Psaty *et al*., 2003).

This study uses panel data from an international market research company serving the pharmaceutical industry. The doctors' panel consists of a stratified sample of 283 family

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[1] Factor analysis permits the researcher to work with a larger set of competitive offerings when compared to nonmetric multidimensional scaling techniques; the perceptual maps resulting from factor analysis are easier to interpret by decision makers compared with those arising from correspondence analysis.

[2] Diuretics reduce the volume of blood by increasing the flow of urine excretion; Betablockers slow down the heart beat; Calcium Antagonists relax the blood vessels by blocking the flow of the calcium ions into the muscles; ACE inhibitors block angiotensin converting enzyme (ACE) to prevent the formation of angiotensin II, which is a potent constrictor of blood vessels; and Alphablockers block alpha-1 adrenergic receptors in blood vessels, causing vasodilatation.

doctors working for the UK National Health Service (NHS), balanced to represent the UK population of family doctors (general practitioners). Family doctors were selected on the basis of their regional distribution across the UK.

Family doctors working for the NHS prescribe around 80 % of all antihypertensive drugs sold in UK. Participating doctors regularly complete a quarterly twenty-page questionnaire; data in this research refers to the first quarter. This secondary data were highly appropriate for the research, since it used a suitable sample and asked suitable questions about attitude, reported prescribing frequency and demographic details of doctors and their practices. The information relates to the main prescription drugs from the different antihypertensive classes and includes information on all relevant needs concerning their prescription. All of the 283 doctors returned filled questionnaires. Cases where more than 15 % of the data were missing were specifically excluded. The remaining 232 questionnaires were used in the analysis. Missing data for the attitude and reported prescribing frequency were replaced by the corresponding average value across all doctors, whereas demographic details were left as missing.

Both the sampled drugs and the questions in the questionnaire were selected by pharmaceutical marketing experts specialising in hypertension from the major international drug companies. These companies pay a fee to have their ethical drugs and questions included in the questionnaire. Fourteen main antihypertensive drugs from the major antihypertensive therapeutic drug classes were used, namely two Diuretics (coded as D1 and D2), three Betablockers (coded as BB1, BB2 and BB3), three Calcium Antagonists (coded as CA1, CA2 and CA3), four ACE-inhibitors (coded as ACE1 to ACE4), and two Alphablockers (coded as AB1 and AB2).

A literature review on antihypertensive prescribing was conducted and exploratory interviews with family doctors were carried specifically for this research. These ensured the questionnaire included all important doctors' needs concerning the prescription of antihypertensive drugs. The literature review revealed that all the main antihypertensive prescribing need concepts/variables presented in other studies are measured with the

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variables used in this questionnaire[3]. The variables which were most used in the studies are those related to efficacy, side effects, cost, patient compliance, and approval by colleagues. Efficacy and side effects of the drug were used in all reviewed studies; cost of the drug, either the cost of the drug for the health care system or the cost for the patient, was used in 10 of these studies; patient compliance, either as patient compliance or as dosage schedule, was used in 8 of the reviewed studies; approval by colleagues, was used under the names of approval by colleagues, colleagues' approval, colleague opinion, or acceptance by peers, in 6 studies, namely in those by Denig *et al.* (1993), Denig *et al.* (1988), Chinburapa and Larson (1988), Segal and Hepler (1985), Segal and Hepler (1982), and Harrel and Bennett (1974).

A series of pilot unstructured interviews of approximately one hour with a convenience sample of 6 family doctors confirmed that the three variables not identified in the literature correspond to additional antihypertensive prescribing needs, namely those concerned with the quality of life of the patient (variable "Improves patient's quality of life") and with the medicine's additional beneficial effects (variables "Cardio-Protective Drug" and "Benefits the Whole Cardiovascular System").

Doctors' prescribing attitudes were measured on a seven-point Likert scale (1 = "Strongly agree" to 7 = "Strongly disagree"). The attitude variables names and codes are presented in Table 1. Family doctors were also asked to indicate how frequently they used each drug in the treatment of hypertension, again using a seven-point Likert scale. This type of Likert scales are commonly used in marketing research (e.g. Bruner *et al.*, 2005).

[Insert Table 1]

The data analysis (using SPSS for Windows) used factor analysis to determine the main perceptual dimensions used to evaluate competitive antihypertensive drugs, cluster analysis to identify the different perceived categories of ethical drugs, and multiple

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[3] Greving *et al.*, 2006; Denig *et al.*, 1993; Chinburapa and Larson, 1993; Jernigan, 1991; Chinburapa and Larson, 1988; Denig *et al.*, 1988; Chinburapa *et al.*, 1987; Segal and Hepler, 1985; Epstein *et al.*, 1984; Segal and Hepler, 1982; Lilja, 1976; Harrel and Bennett, 1974.

regression analysis to find the relative importance of the main perceptual dimensions. All multivariate techniques were first run on an analysis sample comprising two thirds of the doctors. They were then run on a validation sample comprising the remaining one third of doctors. The analysis and the validation sample were randomly generated. Tables 2–6 and Figures 1–6 refer to the results obtained from the analysis sample.

4. Determining the Main Perceptual Prescription Drug Choice Dimensions

The perceptual dimensions used by family doctors to evaluate antihypertensive drugs can be identified using factor analysis, a multivariate technique for exploring the interdependence among observed variables (Kim and Mueller, 1978). Exploratory factor analysis was used to reduce, with minimum loss, the information contained in the observed variables into a smaller group of factors, or dimensions (Gorsuch, 1983). Since it can cope with any data distribution, principal components method with varimax rotation was used to identify the few perceptual dimensions that account for most of the variance in the measured perceptual data. According to DeSarbo *et al.* (2007), "this is one of the foremost multivariate methods utilized in marketing and business research for data reduction". Principal components method has, for example, recently been used to identify the main axes of socio-economic development of European regions (Del Campo *et al.,* 2008); investigate how decision makers characterize alternatives in important decisions (Svenson and Halo, 2007); examine basic financial characteristics of banks (Canbas *et al.*, 2005); search for patterns of supply chain practices (Yusuf *et al.*, 2004); and identify the socio-economic development dimensions of a country's territory (Soares *et al.*, 2003).

Principal components analysis was carried out on the analysis sample (two thirds of doctors), with the factor structure then validated on the validation sample (the remaining one third). A table of all doctors and all drugs (vertical axis), and all attribute variables (horizontal axis) was built for each sample, and each table was subjected to the following procedure: (i) the correlation matrix of all variables was used to evaluate the appropriateness of the factor model; (ii) the number of factors to be extracted and the assessment of the model fit with the original data was determined; (iii) varimax rotation, which imposes an orthogonal structure on the data, was applied to make the factors more interpretable; (iv) factor scores for each case were computed for use in subsequent statistical analysis.

The suitability of the data for factor analysis was checked by looking at the correlation matrix for all variables and by computing the Bartlett's (1950) test of sphericity and the Kaiser–Meyer–Olkin (KMO) measure of sampling adequacy (Hair *et al*., 2006). The correlation matrix for the 21 attributes is shown in Table 2; all but 11 correlations in this matrix are significant at the 0.01 level. Seventeen variables have at least one correlation coefficient greater than 0.4, with the remaining four variables having at least one correlation coefficient exceeding 0.3. This is consistent with Kinnear and Gray (1999) who indicate that variables with coefficients greater than 0.3 can be included in the analysis. Therefore, all 21 variables satisfied the conditions for inclusion in the analysis. Bartlett's (1950) test of sphericity was used to test the hypothesis that the correlation matrix is an identity matrix. With a value of 15706.2, the probability associated with this test is smaller than 0.001. The hypothesis was rejected, meaning that it is unlikely that the correlation matrix is an identity matrix and that the matrix is appropriate for factor analysis. Finally, the KMO value of sampling adequacy was found to be 0.88, a figure that Kaiser and Rice (1974) classify as meritorious, suggesting the data are suitable for factor analysis.

[Insert Table 2]

The criteria considered to determine the number of factors to extract were the (i) eigenvalue criterion; (ii) the scree test criterion (Catell, 1966); (iii) the percentage of variance criterion; and (iv) the interpretability of the factor structure solution (Hair *et al*., 2006; Kline, 1994). The eigenvalue criterion suggests retaining all factors with eigenvalues greater than 1. Five of the eleven factors extracted in the principal components analysis satisfied this criterion (see Table 3).

[Insert Table 3]

The scree test indicates that the maximum number of factors to extract is given by "the point at which the curve first begins to straighten out" (Hair *et al*., 2006). In general, the scree test suggests the extraction of up to three more factors than the eigenvalue criterion. Since a straight line would fit the eigenvalues of factors 6–21, the scree plot in Figure 1 indicates that a maximum of six factors should be extracted. However, it could

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be argued that the "elbow" in the eigenvalues might suggest that three factors should be extracted; for this reason the three factor solution was also evaluated. This kind of interpretation is appropriate since researchers recognised that the scree test criterion is not an exact measure, and "involves judgment of where the discontinuity in eigenvalues occurs" (Tabachnick and Fidell, 2007).

[Insert Figure 1]

The percentage of variance criterion recommends extracting the factors accounting for at least 60 % of the original variance, a cut-off point which is normally accepted as satisfactory for social science research. According to this criterion at least five factors should be extracted (see Table 3).

Finally, the factor solutions identified as a consequence of the first three criteria were subjected to the interpretability test. The ability to interpret and assign meaning to the factors is an important consideration in determining how many factors to extract (Hair *et al*., 2006). Principal components analysis with varimax rotation was used to derive four alternative factor structures retaining three, four, five and six factors. The most readily interpretable solution was obtained when five factors were retained (see Table 4).

[Insert Table 4]

Considering the assessment of the selected factorial structure, Hair *et al*. (2006) suggest that factor loadings greater than 0.30 are considered minimally acceptable, whereas loadings greater than 0.50 are considered significant. Following the procedure used by Lattin *et al*. (2003), to make it easier to read the factor structure factor loadings greater than 0.40 are displayed in bold in Table 4. Assessing this model reveals a number of positive features. Firstly, all variables have significant loadings, except three variables which have acceptable factor loadings of between 0.40 and 0.50. Secondly, seventeen variables load highly on only one factor, whereas only four variables load highly on two factors. Thirdly, the five factor solution accounts for between 49 % and 73 % of the variance for each individual variable. Finally, the first five factors account for more than 60 % of the total variance of the original variables.

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Since four of the variables load highly on more than one factor, the question of discriminant validity is raised. However, as three of these variables (UDC, ACP, and EFS) clearly have higher loadings on one factor, and given the overall intuitive logic of the factor structure, this is not considered to be a major concern (Hair *et al*., 2006).

Turning to the labelling of factors, the first factor, which accounts for around 19 % of the total variance, is called the "**additional beneficial effects**" of the drug, since the variables with higher loadings on this factor are "benefits the whole cardiovascular system", "regresses left ventricular hypertrophy", and "has a beneficial effect on serum lipid profile" (factor loadings between 0.65 and 0.73). Lower scores on this factor mean higher "additional beneficial effects".

The second factor, which accounts for 13 % of total variance, is named "**long term efficacy**" of the drug. Two variables with high loadings are "offers long term control of hypertension" and "effectively lowers systolic blood pressure" (0.73 and 0.60 respectively). It seems that long term treatment of hypertension is easily achieved with drugs which have simpler dosage regime, since the variable "a very simple dosage regime" also loads highly only on this factor, with a value of 0.63. Lower scores on this factor reflect higher "long term efficacy".

Factor three accounts for around 12 % of total variance and is named perceived "**medical support**", because it reflects the medical support the drug receives from professionals. High loadings on this factor are for variables "first line treatment in hypertension", and "widely recommended by local consultants" (0.80 and 0.57 respectively). Drugs with high "medical support" are also highly useful for mild hypertension, since the variable "a useful drug for use in mild cases of hypertension" also loads highly on this factor (loading of 0.76). Lower scores on this factor reflect higher perceived "medical support".

The fourth factor, which accounts for about 9 % of total variance, clearly reflects the "**adverse side effects**" of the drug. The only three variables that load high on this factor are all related to adverse side effects of antihypertensive drugs. The two variables that load highly on this factor are "tends to cause postural hypotension" and "occasionally

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will produce severe side effects" (0.73 and 0.72 respectively). Lower scores on this factor reflect higher "adverse side effects".

Only the variable "very suitable for asthmatic and bronchitic patients" loads highly on factor five (0.81). This factor, which accounts for around 8 % of total variance, thus reflects the "**asthmatic and bronchitic suitability**" of the drug for patients with these additional conditions, is named accordingly. Lower scores on this factor mean the drug is more suitable for asthmatic and bronchitic patients.

Factor scores were computed for each case, so that each was represented by a smaller set of scores based on the derived perceptual dimensions. These scores, which were obtained using the regression method, have a mean of zero and a standard deviation of one.

A five factor solution was also found when the validation sample was subjected to the same analysis with an almost identical factor structure being produced. There were similar factor loadings, the percentage of variance explained was similar (16.3 %, 14.8 %, 13.4 %, 7.5 %, and 7.4 % for rotated factors F1, F2, F3, F4, and F5 respectively), as was the cumulative percentage of variance explained (59.5 %), and communalities (with values between 0.48 and 0.72).

5. Building Perceptual Maps Showing the Perceived Competitive Positions of Prescription Drugs

The competitive positions of the 14 antihypertensive drugs were established by deriving perceptual maps displaying each brand's average factor score, across all doctors, on each perceptual dimension (see Figures 2–4). Figure 2 shows the perceptual map revealing the competitive positions of the ethical drugs analysed in relation to dimensions F1 - "additional beneficial effects" and F2 - "long term efficacy"; Figure 3 provides similar information based on dimensions F1 and F3 - "medical support", whereas the perceptual map show in Figure 4 is based on dimensions F4 - "adverse side effects" and F5 - "asthmatic and bronchitic suitability". These perceptual maps offer a useful way of viewing the perceived relative positions of the various ethical drugs along the five derived dimensions. They also show the main perceived differences between individual and categories of ethical drugs.

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Figure 2 reveals that ACE2 is perceived as delivering the best "additional beneficial effects" of all ethical drugs in the sample, whereas the diuretic D1 is at the other extreme of this perceptual dimension. Figure 2 reveals that ACE3, ACE4, ACE1 and CA2 constitute the group of prescription medicines best perceived conjointly in terms of dimensions F1 and F2. Figure 3 shows that three drugs from three different antihypertensive categories are perceived to display the best "medical support", namely the calcium antagonist CA1, the diuretic D1, followed by the betablocker BB3. Turning to Figure 4, the lowest score of ACE2 on dimension F4 indicates that this is the antihypertensive with the highest perceived "adverse side effects".

The various classes of antihypertensive drugs, as doctors perceive them, are also plotted in Figures 2–4. These groups of drugs where identified using the following cluster analysis approach on the doctors' derived perceptions (Lattin *et al.*, 2003; Punj and Stewart, 1983). First, a hierarchical cluster analysis, using Ward's method (Ward, 1963) with the squared Euclidean measure – which is the distance measure that should be used with this method (Everitt *et al.*, 2001), was performed on the rotated factor scores for each drug. This solution was then confirmed with a non-hierarchical clustering procedure (K-means clustering) using the centroids from Ward's method as seeds. For the analysis sample (66 % of doctors) four clusters gave the best statistical and interpretative solution (see the dendrogram in Figure 5). The K-means clustering solution produced the same results as for Ward's method where four clusters were extracted. The same results were produced for the validation sample.

[Insert Figure 2]

[Insert Figure 3]

[Insert Figure 4]

[Insert Figure 5]

Looking at Figure 5, from left to right, the first two categories to merge are the Alphablockers and Calcium Antagonists, resulting in the biggest of the four clusters; the

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second cluster corresponds to the ACE class; the third cluster groups the two Betablockers BB3 and BB1; while the final cluster groups together the two diuretic drugs, D1 and D2. Only the betablocker BB2 was not correctly classified in its class, appearing with the Alphablockers and the Calcium Antagonists. The diuretic group of drugs is the last to merge, meaning that is perceived to be the antihypertensive therapeutic class that most differs from the other drugs classes in the analysis.

Figure 2 reveals that the first perceptual dimension clearly separates the ACE group, which is viewed as offering the best "additional beneficial effects", from the diuretic group, which is positioned at the other extreme of this dimension. Diuretics are also perceived to be the therapeutic group of ethical medicines with the worst "long term efficacy". On the other hand, the fourth derived perceptual dimension reveals that the Diuretics group is perceived to produce the more desirable "adverse effects" of all antihypertensives (see Figure 4). Figure 4 also shows that Betablockers, which have the highest scores along the fifth dimension, are perceived to be the worst group in terms of "asthmatic and bronchitic suitability"; whereas Diuretics are the most appropriate drugs for hypertensive patients who suffer from these diseases.

The Betablockers category, with variations on dimensions two, three, four and five, is the drug class with the biggest perceived differences. The Alphablockers category, each of which have similar, small differences along all dimensions, is perceived as the most homogeneous. The ACEs have the greatest variations along dimensions two and three, the Calcium Antagonists along dimensions three and four, and the Diuretics along the third dimension. This should be viewed in the context that the biggest variations in drugs within all drug classes always occur on a set of dimensions that include dimension 3.

6. Determining the Relative Importance of the Main Evaluative Dimensions

A form of multiple regression analysis called preference regression (Urban and Hauser (1993) was performed to determine the relative importance of the main evaluative dimensions. The factor scores obtained for each doctor and drug were used as independent variables, with "reported prescribing frequency" (which can be regarded as a surrogate variable for drug market share) as the dependent variable. This analysis was first conducted on the analysis sample (66 % of doctors), before being run on the

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validation sample. As suggested by Hair *et al*. (2006), model estimates from both samples were then compared for differences in the significant variables included, their sign, size, and relative importance. A table with all doctors and all drugs (vertical axis), and the five derived perceptual dimensions (horizontal axis) was built in each case.

The multiple regression model assumes the existence of a linear relationship between the dependent and independent variables. To assess this assumption, the scatter-plots of the individual, dependent and independent variables were visually inspected. This observation did not indicate any non-linear relationships between the dependent and independent variables. The stepwise procedure was then used to estimate the regression model. As Table 5 shows, the adjusted coefficient of determination (adjusted R^2) increases from 42.8 % to 43.0 % when Factor 5 is added to the model and from 43.0 % to 43.1 % when Factor 4 is added. Consequently, only the first three factors are used in the final derived model. This is a more parsimonious model and is therefore considered the best model using factors as independent regression variables.

[Insert Table 5]

Results of the multiple regression model derived with the first three factors are shown in Table 6. Multicollinearity is not a problem in this regression model since the independent variables, the varimax rotated factors, are by definition uncorrelated. Consequently, the tolerance and VIF values in Table 6 are 1.0, as expected. This regression model was estimated after nine outliers (observations showing standardised residuals with absolute value greater than 3.0) had been excluded, which slightly improved the regression results – e.g., the adjusted R^2 for the model with three factors in Table 5 rose from 0.428 to 0.452, in Table 6.

Equation (1) shows the derived linear regression model with the three most important factors explaining 45 % of the variation in "reported prescribing frequency".

$$(1) \quad \text{RPRESC} = 4.70 + 0.54 \text{ F1} + 0.49 \text{ F2} + 1.05 \text{ F3}; \quad R^2 \text{ Adj.} = 0.45$$
$$(152.75) \, (17.68) \quad (16.08) \quad (34.22)$$

As expected, "reported prescribing frequency" increases as the first dimension "additional beneficial effects" increases, with the increase of the second dimension

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"long term efficacy", and with the increase of the third dimension perceived "medical support". Looking at the Beta values shown in Table 6, the most important variable in this regression model is Factor 3, with a figure of 0.55, approximately double the weight of Factor 1 and Factor 2.

[Insert Table 6]

To verify whether assumptions on which the regression analysis model rests are met, the linearity, homocedasticity, independence of residuals and normality assumptions were examined. Linearity of the overall equation can be judged by observing the plot of standardised residuals against the predicted values of the independent variable "reported prescribing frequency" (Hair *et al.*, 2006). This plot revealed no non-linear patterns within the data, suggesting that the application of the linear model is adequate. Moreover, the standardised partial regression plots for each independent variable showed no non-linear patterns. The plots also reveal that the relationship of Factor 3 is the most well linearly defined. The violation of equality of variance assumption can be checked by plotting the standardised residuals against the independent and dependent variables, then observing increases or decreases in the spread of residuals as the values of these variables change. As the standardised residuals plots for each independent variable revealed no increasing or decreasing pattern of residuals, this assumption is validated. To check the independence of residuals, the residuals were plotted against all independent variables and the case number variable. No pattern was found, suggesting that residuals are independent from one observation to another. A visual inspection of the normal probability plot of the standardised residuals revealed expected versus observed values close to the diagonal, suggesting it is reasonable to assume approximate normality of regression residuals – see Figure 6.

[Insert Figure 6]

Validation of the regression model was achieved by comparing the stepwise results from equations (1) and (1a), which are from different samples, to ensure robustness:

$$(1a) \quad RPRESC = 4.78 + 0.55 \ F1 + 0.40 \ F2 + 1.20 \ F3; \quad R^2 \ \text{Adj.} = 0.49.$$
$$(114.03) \ (13.17) \quad (9.21) \quad (28.97)$$

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7. Using Doctors' Perceptions to Support Strategic Marketing Decisions Concerning Ethical Drugs

The perceptual analysis enables the effects of positioning strategies to be monitored and better competitive positions for ethical antihypertensive drugs to be identified. Using ACE2 and ACE3 as an example, the perceptual maps show that ACE2 is beaten by ACE3 on the second dimension, "long term efficacy". This is because ACE3 is perceived to have a simpler dosage regime than ACE2. In fact, both drugs have similar scores on all except one of the attributes that load high on the second perceptual dimension. The exception is the variable "a very simple dosage regime", with ACE3 and ACE2 showing average scores of 2.5 and 3.7, respectively. These perceptions reflect reality, since ACE3 was designed to have a simpler dosage regime than ACE2.

The situation relating to ACE1 and ACE4, which both contain exactly the same chemical entity, should also be considered. As Company A already had the leading ACE3 in its portfolio when ACE1 was invented, it decided to position ACE1 as particularly suitable for elderly patients. Meanwhile Company B, which licensed the same chemical entity from Company A, marketed ACE4 as a general ACE. As Figures 2–4 reveal, doctors perceive the two brands differently, even though they contain the same active ingredient.

The derived perceptual maps also reveal that there is a strategic gap for a new antihypertensive that excels in both dimensions F1 and F3 (see Figure 3). Alternatively, this gap could de fulfilled, for example, if it would be possible to improve considerably the score of CA1 on the dimension F1, since this drug already displays the best "medical support", or by improving considerably the score of ACE2 on dimension F3, since ACE2 already offers the best "additional beneficial effects" of all antihypertensives in sample.

Perceptual maps are helpful to identify those ethical drugs which are not differentiated in the minds of prescribers – those which are those located close to the origin. One such example is CA2 which is always very close to the origin in Figures 2–4.

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Pharmaceutical marketing managers can use the linear model derived from the analysis to guide the search for better competitive positions for antihypertensive drugs. The relationships captured in equation (1) can be used to explore alternative ways to increase the "reported prescribing frequency" and market share of brands. Taking ACE4 as an example, its "reported prescribing frequency" can be improved more effectively if it is possible to enhance the drug's scores along the dimensions F3 - "medical support", F1 - "additional beneficial effects" and F2 - "long term efficacy", by this sequence (see Beta values in Table 6).

Where marketing managers are primarily concerned with competition within the ACE group, attention should be focused on the third and first dimensions, since ACE4 is already perceived as the best option on dimension two (see Figures 2 and 3). Looking at the first dimension, ACE4 has to improve its score along one or more of the original variables which load highly on this dimension. However, analysis of these original variables revealed that ACE4 already has similar scores to its competitors. This implies that unless new information about the drug is provided, it may be difficult to improve the scores for these variables. To improve its score along the third dimension, the analysis of the original variables that load high on dimension three revealed that the variable where ACE4 is at a greater competitive disadvantage in the ACE group is the variable WRB. Therefore efforts are needed to improve the degree to which ACE4 is perceived to be "widely recommended by local consultants".

8. Conclusions, Limitations and Suggestions for Further Work

This study has been the first to apply factor analysis to develop perceptual maps revealing the key choice dimensions and perceived competitive positions of ethical pharmaceutical brands. In addition, this is the first time that multivariate perceptual mapping methods have been used to investigate the antihypertensives market. Moreover, this research has analysed a large set of fourteen ethical drugs, contrasting to previous studies which have produced perceptual maps for a maximum of seven competing ethical drugs. As has been argued, such simultaneous analysis of a large set of prescription drugs might benefit pharmaceutical managers who are operating in the most competitive ethical markets. The methodology used in this research aims to improve the knowledge of how doctors choose the drugs they prescribe and to support strategic marketing decisions in the ethical pharmaceutical industry.

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Factor analysis has revealed that UK family doctors use five dimensions to evaluate competitive antihypertensive drugs. According to Urban and Hauser (1993) "there is evidence that customers tend to simplify judgments by reducing dimensionality to prevent cognitive strain and information overload". The fact that doctors in this research use a small number of dimensions to perceive prescription drugs suggests that doctors share this behaviour with customers in general.

These dimensions are the "additional beneficial effects" of the drug, the "long term efficacy" of the drug, the perceived "medical support" the drug receives from professionals, the "adverse side effects" of the drug, and finally, the "asthmatic and bronchitic suitability" of the drug. These results[4], in particular the dimensions "long term efficacy" and "adverse side effects", corroborate the findings obtained by Neidell (1969), who also found two similar perceptual dimensions, one related to potency/effectiveness and the other to undesired side effects of the ethical brand. In the study by Hurrell *et al.* (1997), one of the perceptual map's dimensions was related to the "strength" of the prescription drug. This might indicate that doctors use the dimensions related to efficacy and side effects (undesired) to perceive and evaluate prescription drugs across various ethical markets.

Perceptual maps were then built showing the perceived competitive positions of the sampled ethical brands, using average factor scores on each of the derived perceptual dimensions. Cluster analysis revealed that doctors perceive there to be four distinctive categories of antihypertensives. One cluster groups together Alphablockers and Calcium Antagonists; a second cluster corresponds to the ACE group; a third cluster groups the two Diuretics; and a fourth cluster groups two of the Betablockers. Only one betablocker medicine was not correctly classified in its class.

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[4] Results of the present research are not comparable to those obtained by DeSarbo *et al.* (2002) who derived a two dimensional map built on preference data alone. Consequently, their map is noticeable different from the maps derived in the present research. DeSarbo *et al.* (2002) make the following observations about their dimensions, commenting that "the horizontal dimension reflects brand ingredients" and the "vertical dimension correlates highly with market share".

Multiple regression analysis using the scores of the derived perceptual dimensions as independent variables, and "reported prescribing frequency" as the dependent variable, was carried out to determine the relative importance of the main evaluative dimensions. The findings show that UK family doctors prefer antihypertensive drugs with higher perceived "additional beneficial effects", with higher perceived "long term efficacy"[5], and with higher perceived "medical support". Moreover, it was found that the most single important dimension in determining "reported prescribing frequency" is the perceived "medical support". Results have shown that the regression model with the first three main perceptual dimensions explains 45 % of the total variance of the dependent "reported prescribing frequency" variable. The methodology used in this research provides pharmaceutical marketing managers with the means to identify more appropriate competitive positions for ethical antihypertensives.

This research contributes to the strategic marketing and operational research knowledge fields by showing that multivariate approaches which have been successfully used in other industries can be applied to the ethical pharmaceutical market. More specifically the work demonstrates that these quantitative approaches can be used to refine the targeting and positioning of drugs to the doctors who prescribe them. This is possible because the analysis improves existing knowledge about how doctors choose the drugs they prescribe.

This research has practical implications for the ethical pharmaceutical industry, demonstrating a multivariate methodology which is new to the industry. The application provides pharmaceutical managers with a tool for improving strategic marketing decisions concerning ethical drugs. Finally, this work is relevant to governments and healthcare bodies involved in shaping policy on prescribing. The decisions these policy makers take may force doctors to alter their prescribing habits. In such circumstances it is important to understand how the perceptions and preferences of doctors for the medicines they prescribe will change. This methodology can be used to monitor the

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[5] This finding is not in line with research results reported by Neidell (1969) suggesting that the average doctor prefers ataractic drugs with intermediate rather than higher potency/effectiveness. On the other hand, he also reported that doctors prefer anorectic drugs with higher potency.

effects of health care policies on ethical drugs on the perceptions, preferences and actual prescribing habits of doctors.

There are a number of opportunities for further research which builds upon the findings presented here. Given that this research has used self-reported rather than actual prescribing frequency, it would be appropriate to consider how well self-reported measures adhere to actual prescribing behaviour. The research also suffers from general criticisms about compositional studies, since doctors have been asked direct questions about attribute variables. This raises the question of whether doctors actually use the attributes included in the questionnaire when making prescribing decisions, or whether some would not have been considered had they not been included in the questions. Future research using decompositional approaches would be welcomed to clarify this issue and to verify whether compositional and decompositional approaches lead to the same results, where prescription drugs are analysed. It would also be interesting to compare the results from the vector model approach with those resulting from an ideal model approach. This would help examine whether doctors use perceptual dimensions where "more (or less) is better" fits the prescriber population as a whole. Research examining the effect of variables which intervene between intention and behaviour and change prescribing intention is also warranted.

The methodology adopted in this paper could be applied across a range of situations, including to different segments of doctors, to those working in other countries or in different types of healthcare organizations. This would enable doctors subjected to different prescribing policies to be studied. A longitudinal research design would enable changing perceptions over time to be examined. Other ethical drugs and different perceptual variables could also be examined. Finally, other methodologies should be tried; in particular structural equation modelling could be used to test whether the factor and regression results empirically obtained in this research hold in other prescribing situations.

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Code	Variable name
OLT	Offers long term control of hypertension
ACP	A cardio protective drug
HRI	Has relatively infrequent side effects
EFS	Effective for severe cases of hypertension
ARE	A relatively expensive drug
VSA	Very suitable for asthmatic and bronchitic patients
AVS	A very simple dosage regime
TTC	Tends to cause postural hypotension
VSE	Very suitable for elderly patients
WRB	Widely recommended by local consultant
IQL	Improves patient's quality of life
UFM	A useful drug for use in mild cases of hypertension
WSB	Well supported by clinical trials
VSY	Very suitable for younger hypertensives
OWP	Occasionally will produce severe side effects
FLT	First line treatment in hypertension
UDC	Useful for difficult hypertensive cases
ELS	Effectively lowers systolic blood pressure
BSL	Has a beneficial effect on serum lipid profile
RLV	Regresses left ventricular hypertrophy
BWC	Benefits the whole cardiovascular system

Table 1 - Variables used to evaluate ethical drugs

	OLT	ACP	HRI	EFS	ARE	VSA	AVS	TTC	VSE	WRB	IQL	UFM	WSB	VSY	OWP	FLT	UDC	ELS	BSL	RLV	BWC
OLT	1.00																				
ACP	0.30	1.00																			
HRI	0.33	0.18	1.00																		
EFS	0.55	0.40	0.19	1.00																	
ARE	0.22	0.20	0.07	0.35	1.00																
VSA	0.19	-0.14	0.34	0.11	0.22	1.00															
AVS	0.33	0.06	0.29	0.20	0.13	0.24	1.00														
TTC	0.09	0.11	-0.15	0.23	0.25	0.01	-0.05	1.00													
VSE	0.28	0.11	0.45	0.21	0.07	0.41	0.34	-0.09	1.00												
WRB	0.28	0.25	0.16	0.35	0.09	0.09	0.07	0.06	0.28	1.00											
IQL	0.36	0.31	0.39	0.39	0.24	0.31	0.25	0.07	0.47	0.34	1.00										
UFM	0.23	0.07	0.39	0.03	-0.13	0.20	0.24	-0.17	0.50	0.26	0.34	1.00									
WSB	0.48	0.24	0.27	0.38	0.14	0.15	0.25	-0.01	0.29	0.40	0.35	0.26	1.00								
VSY	0.48	0.37	0.43	0.48	0.26	0.31	0.22	0.06	0.45	0.40	0.55	0.36	0.38	1.00							
OWP	0.15	0.14	-0.22	0.17	0.18	-0.11	-0.05	0.38	-0.23	0.03	-0.09	-0.18	0.10	0.00	1.00						
FLT	0.39	0.15	0.32	0.24	-0.05	0.15	0.25	-0.07	0.42	0.42	0.36	0.60	0.36	0.51	-0.03	1.00					
UDC	0.45	0.39	0.18	0.68	0.36	0.23	0.17	0.22	0.27	0.38	0.46	0.08	0.36	0.54	0.16	0.30	1.00				
ELS	0.47	0.26	0.14	0.43	0.28	0.16	0.23	0.18	0.19	0.23	0.34	0.12	0.36	0.37	0.23	0.30	0.46	1.00			
BSL	0.19	0.27	0.18	0.28	0.26	0.27	0.05	0.17	0.19	0.20	0.30	0.11	0.16	0.33	0.07	0.16	0.40	0.23	1.00		
RLV	0.31	0.33	0.20	0.39	0.30	0.21	0.12	0.19	0.23	0.26	0.43	0.13	0.26	0.41	0.12	0.21	0.48	0.30	0.39	1.00	
BWC	0.40	0.44	0.32	0.37	0.21	0.23	0.13	0.04	0.31	0.36	0.53	0.22	0.35	0.53	0.05	0.30	0.46	0.30	0.39	0.52	1.00

Table 2 – Correlation Matrix for the 21 Variables

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Factor	Eigenvalue	% of variance	Cumulative % of variance
1	6.4	30.6	30.6
2	2.5	12.1	42.6
3	1.4	6.7	49.4
4	1.2	5.9	55.3
5	1.0	4.8	60.1
6	0.8	4.0	64.1
7	0.7	3.5	67.6
8	0.7	3.2	70.8
9	0.7	3.2	74.0
10	0.6	3.1	77.1
11	0.6	3.0	80.0

Table 3 - First Eleven Factors Extracted using Principal Components Method

Var. Code	Variable	F1	F2	F3	F4	F5	Communality
BWC	Benefits the whole cardiovascular system	**0.73**					0.62
RLV	Regresses left ventricular hypertrophy	**0.69**					0.53
BSL	Has a beneficial effect on serum lipid profile	**0.65**					0.53
UDC	Useful for difficult hypertensive cases	**0.63**	**0.43**				0.64
ACP	A cardio protective drug	**0.62**				**-0.44**	0.66
IQL	Improves patient's quality of life	**0.58**					0.57
VSY	Very suitable for younger hypertensives	**0.57**					0.63
ARE	A relatively expensive drug	**0.41**					0.55
OLT	Offers long term control of hypertension		**0.73**				0.65
AVS	A very simple dosage regime		**0.63**				0.58
ELS	Effectively lowers systolic blood pressure		**0.60**				0.52
EFS	Effective for severe cases of hypertension	**0.50**	**0.60**				0.65
WSB	Well supported by clinical trials		**0.56**				0.49
FLT	First line treatment in hypertension			**0.80**			0.73
UFM	A useful drug for use in mild cases of hypertension			**0.76**			0.68
WRB	Widely recommended by local consultant			**0.57**			0.52
VSE	Very suitable for elderly patients			**0.46**		**0.46**	0.62
TTC	Tends to cause postural hypotension				**0.73**		0.60
OWP	Occasionally will produce severe side effects				**0.72**		0.60
HRI	Has relatively infrequent side effects				**-0.49**		0.55
VSA	Very suitable for asthmatic and bronchitic patients					**0.81**	0.72
	Percentage of total variance explained (%)	19	13	12	9	8	

Table 4 - Five Factor Solution obtained with Principal Components Method and Varimax Rotation

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.535 (a)	.287	.286	1.6096	.287	845.349	1	2105	.000
2	.604 (b)	.365	.364	1.5189	.078	259.904	1	2104	.000
3	.655 (c)	.429	.428	1.4410	.064	234.623	1	2103	.000
4	.656 (d)	.431	.430	1.4388	.002	7.489	1	2102	.006
5	.657 (e)	.432	.431	1.4375	.001	4.857	1	2101	.028

a. Predictors: (Constant), F3
b. Predictors: (Constant), F3, F1
c. Predictors: (Constant), F3, F1, F2
d. Predictors: (Constant), F3, F1, F2, F5
e. Predictors: (Constant), F3, F1, F2, F5, F4
f. Dependent Variable: RPRESC

Table 5 - Stepwise Multiple Regression Model Summary, with Five Factors as Independent Variables

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Dependent Variable: RPRESC
Variable(s) Entered: F1, F2, F3

Multiple *R*	0.673	
***R* Square**	0.453	
Adjusted *R* Square	0.452	
Standard Error	1.408	

ANOVA

	df	Sum of Squares	Mean Square	*F*	Sig.
Regression	3	3440.174	1146.725	578.364	0.000
Residual	2094	4151.784	1.983		

Variable	Variable Name	B	Std. Error	Beta	Tolerance	VIF	*t*	Sig.
F1	Additional beneficial effects	0.542	0.031	0.286	1.000	1.000	17.678	0.000
F2	Long term efficacy	0.493	0.031	0.260	1.000	1.000	16.076	0.000
F3	Medical support	1.054	0.031	0.553	1.000	1.000	34.218	0.000
(Constant)		4.696	0.031				152.750	0.000

Table 6 - Regression Estimates of "Reported Prescribing Frequency", with Three

Factors as Independent Variables (with the outliers removed)
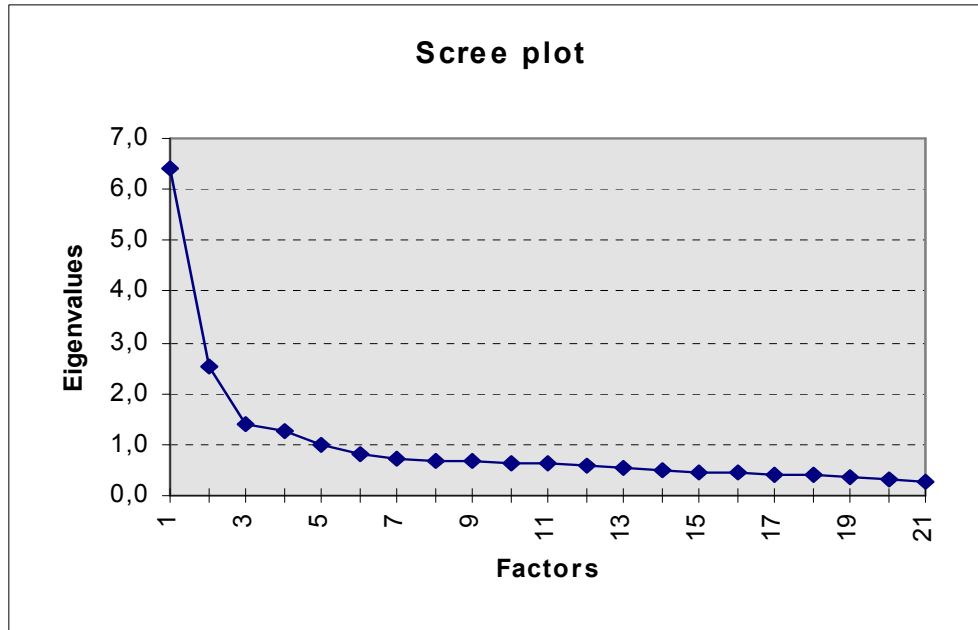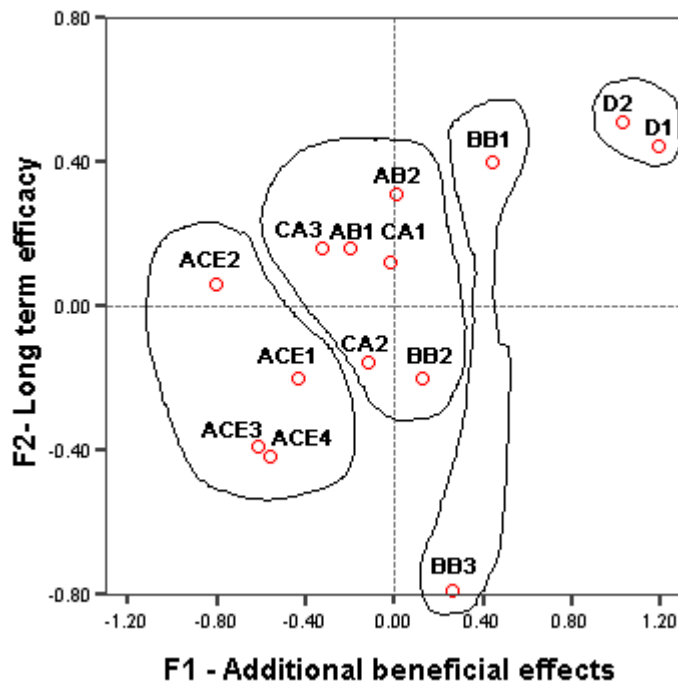
36

Figure 1 - Scree Plot

Figure 2 - Perceptual map "Additional beneficial effects" vs "Long term efficacy"
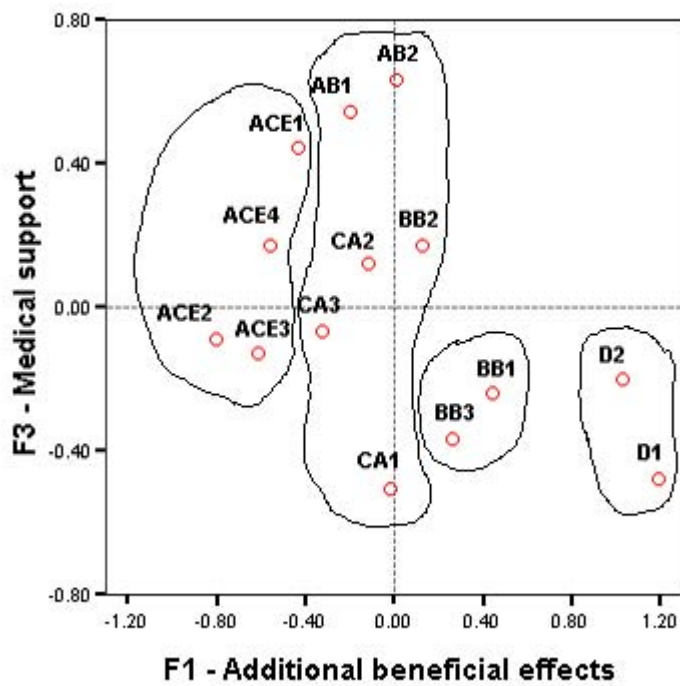
38

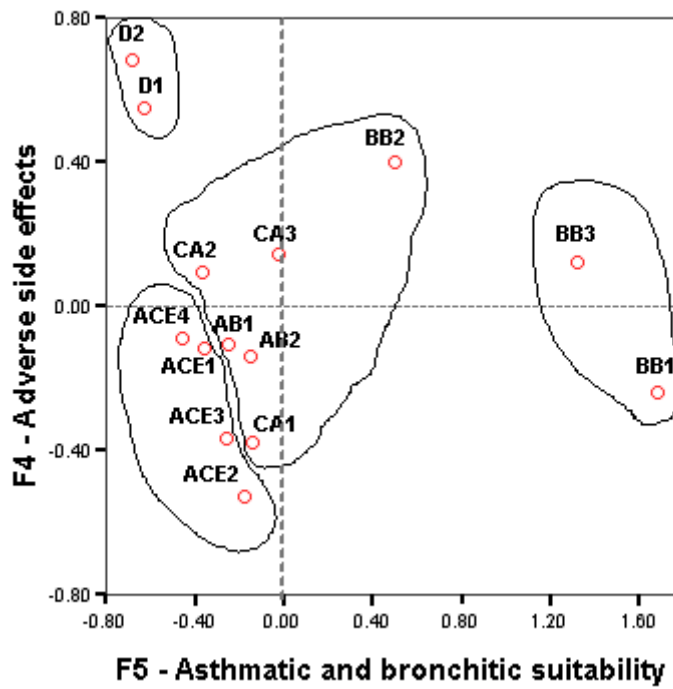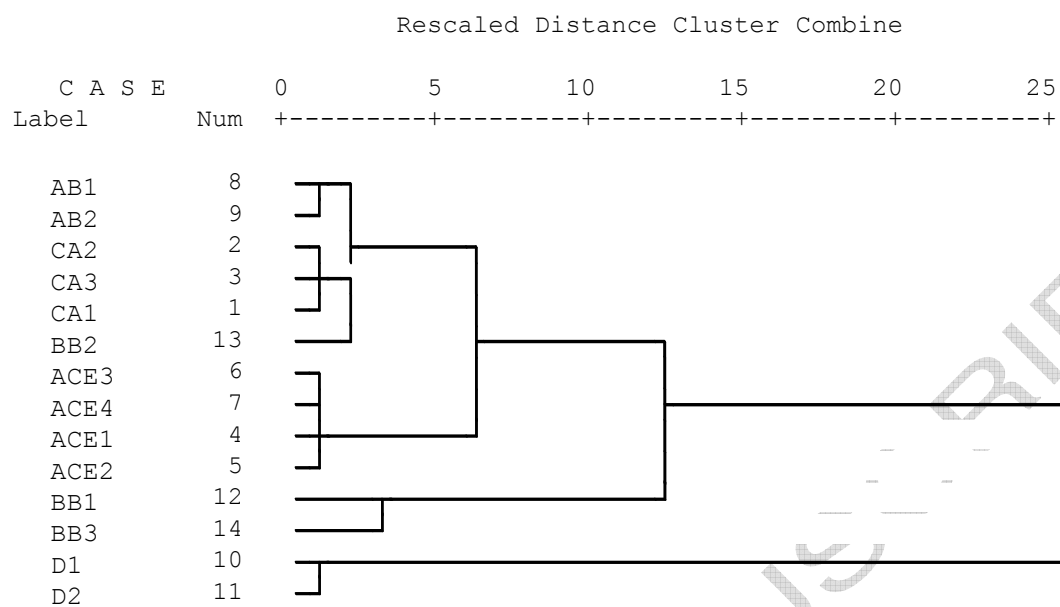**Figure 3 - Perceptual map "Additional beneficial effects" vs "Medical support"**

Figure 4 - Perceptual map "Asthmatic and bronchitic suitability" vs "Adverse side effects"

```
                        Rescaled Distance Cluster Combine

     C A S E           0         5        10        15        20        25
     Label     Num     +---------+---------+---------+---------+---------+

        AB1      8     ─┐ ┌─┐
        AB2      9     ─┘ │ │
        CA2      2     ─┐ │ │
        CA3      3     ─┤ │ │
        CA1      1     ─┘ │ │
        BB2     13     ───┘ │
        ACE3     6     ─┐   │
        ACE4     7     ─┤   │
        ACE1     4     ─┤   │
        ACE2     5     ─┤   │
        BB1     12     ─┘   │
        BB3     14     ─────┘
        D1      10     ─────────────────┐
        D2      11     ─────────────────┘
```
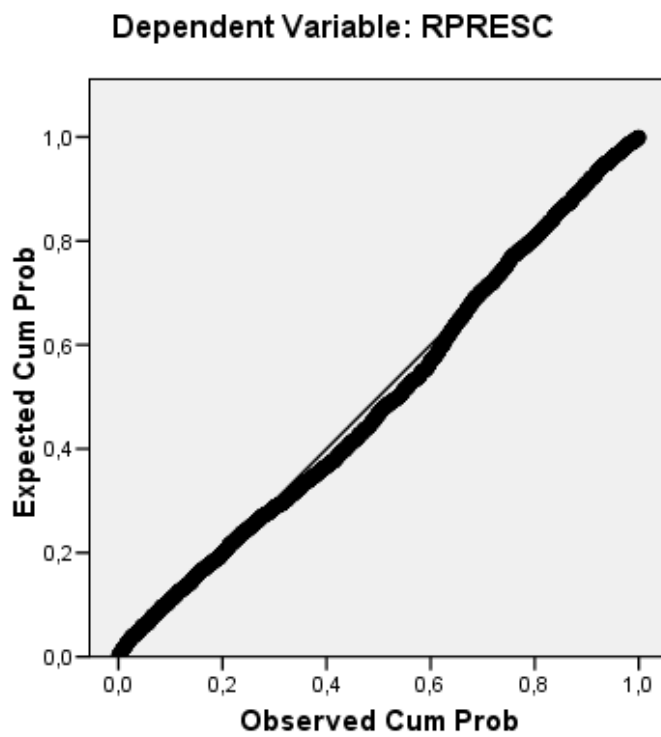
Figure 5 - Dendrogram from the Ward's Method

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Figure 6 – Normal Probability Plot of Regression Standardised Residuals