An Investigation of the Congruency of the Dimensions Underlying Consumers' Perceptions and Preferences in Multidimensional Scaling

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ABSTRACT

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Consumer perceptions and preferences are two critical constructs in marketing research because they are theorized to affect consumers' judgements, intentions to buy and actual purchase behavior. Recently, several researchers in multidimensional scaling (MDS) argued for the joint analysis of the perception and preference data collected from the same sample implicitly assuming that the stimulus spaces for perceptions and preferences were similar in terms of number of dimensions and coordinate values.

Three studies are conducted to test this assumption. It is hypothesized that in MDS, stimulus spaces for perceived similarity data and preferences data would be congruent in terms of the number of dimensions and coordinate values for: (1) those stimuli that could be naturally described in terms of continuous attributes, and (2) for stimuli that are high in the choice hierarchy but (3) not for stimuli that are low in the choice hierarchy. The findings confirm the hypotheses regarding the first two types of stimuli but not the third one. Indeed, the stimulus spaces based on the perceptual and preference data for all three types of stimuli were similar in terms of the number of dimensions, estimated coordinate values and the meaning of the dimensions. This finding encourages further research regarding the development of MDS models jointly using a variety of different measures involving perceptions of similarity, ratings of attributes, and preferences. Limitations of the study, its implications and future research directions are discussed.

CONTENTS

1. INTRODUCTION

Customers' purchasing process is a rich and complex topic that is still not yet fully understood although it has been investigated under various conditions and in numerous studies for more than five decades. Several studies assessing the factors associated with consumers' decision processes nevertheless demonstrated that preferences as well as perceptions are often at the heart of this phenomenon (Bijmolt et al. 1998; Kotler, Armstrong and Cunningham 2002; Assael 1992), ultimately leading to an overall attitude toward a product/service/brand or toward the act of purchasing itself (Myers and Shocker 1981). Hence, consumer perceptions and preferences are two critical constructs in marketing research because they are theorized to affect consumers' intentions to buy and actual purchase behavior (Urban and Hauser 1993; Urban et al. 1996). Also, perceptions of similarity are assumed to serve as input to other consumer judgements, brand and product evaluations, and purchase decisions (Johnson and Puto 1987). For this reason, perceptions of similarity and preferences have been studied extensively within the multidimensional scaling (MDS) tradition (Carroll and Green 1997), a set of models and related software used in marketing research but originally developed in psychometrics (Borg and Groenen 1997; Davison 1983; Green and Carmone 1970; Kruskal and Wish 1978; Schiffman, Reynolds and Young 1981).

Until recently, perceptions and preferences have been studied separately or in parallel in multidimensional scaling (MDS). Recently however, several authors (Carroll and Green 1997; DeSarbo and Wu 2001; MacKay et al. 1995; Ramsay 1980) argued for the ***joint analysis*** of the perception and preference data collected from the same sample in order to generate a spatial representation that summarizes the common underlying structure across these data sets. Such an analysis assumes that the dimensional structures for the perceptions and the preferences are similar. However, the empirical evidence regarding whether such a critical assumption can be supported is scarce in the literature. Furthermore, the findings of only a few studies that examined this issue are at best far from conclusive (DeSarbo and Wu; 2001). Therefore, empirical research concerning the similarity (congruency) of dimensional structures for the perceptions and preferences is critically needed (Glazer and Nakamoto; 1991).

Given this significant gap in the literature and the calls for further research, this study will examine the congruence of dimensional structure for consumer perceptions and preferences in MDS. Since previous studies suggested that MDS is more appropriate for certain sets of stimuli than others (Shepard 1974; Johnson and Puto 1987; Lefkoff-Hagius and Mason 1993; MacKay, Easley and Zinnes 1995), three types of stimuli will be investigated to identify the conditions under which dimensional congruence is likely to be observed. This will allow us to examine the generalizability of our findings to various marketing related stimuli.

The findings of this research are likely to be useful in improving positioning decisions. If the assumption of common dimensions for perceptions and preferences is tenable, the next step would be to identify the kinds of stimuli in marketing for which the assumption holds true. For those stimuli, joint estimation by specifying a joint likelihood for the perception and preference data improves the quality of the resultant probabilistic MDS solutions in terms of positions of the objects and the ideal points, and provides estimates with less bias and variance (Ramsay 1980). This obviously leads to higher confidence in using probabilistic MDS results in positioning decisions and identifying the nature and degree of competition among the stimuli of interest (for example, identifying unique brands, close substitutes, distant competitors, and how they vary from one another). Therefore, our research has direct implications for those marketing decision makers who rely on MDS for positioning decisions, analysis of competitive market structure, market segmentation, branding and management of brand identity, advertising, and introduction of new products (DeSarbo and Wu 2001; Urban and Hauser 1993).

2. LITERATURE REVIEW

More than two decades ago it was proposed in the MDS literature that perceptions and preferences may have common dimensions and the joint analysis of similarity and preference data may improve the quality of the resultant MDS solutions by reducing the bias and variance of the parameter estimates (Ramsay 1980). Some researchers pushed this hypothesis even further and suggested that similarity and preference data could be used interchangeably (Lonial and Van Auken 1982). In order to understand the reasoning underlying these conclusions, a brief review of the MDS literature and how perceptions of similarity and preferences are represented therein is presented next.

2.1. Multidimensional Scaling (MDS) and Representation of Perceived Similarity

MDS refers to a rich set of models and related software to represent proximity and preference data in a multidimensional space. Its origins seem to go back at least to the early 1960's when computers became important working tools and made the complex methodology of MDS computationally feasible (Carroll and Green 1997). Originally, multidimensional scaling was actually an exploratory method. Non-metric MDS was first developed by Roger N. Shepard and later extended by Joseph B. Kruskal (D'Andrade et al. 1972; Mauser 1972). Shepard was in fact the first to demonstrate that it was possible to objectively assess the similarity between types of stimuli such as colors or tones. While previous researchers measured those similarities subjectively, Shepard suggested that the respondents rate pairs of objects based on their perceived similarity. He then developed a computer method that would later be referred to as "non-metric multidimensional scaling". Collectively, these tools, among other things, allow researchers to graphically represent perceptions of similarities or dissimilarities in a visually friendly manner (Borg and Groenen 1997; Shepard 1972; Green and Carmone 1970).

In marketing, MDS is typically used to highlight critical underlying dimensions related to buyers' perceptions of objects (brands, people, places, etc.) and can even be used to detect the existence of clusters among a group of consumers. Moreover, it facilitates product positioning and new product design (Johnson 1971; Shocker and Srinivasan 1979; Urban and Hauser 1993). Finally, an interesting application of MDS is the use of its resulting representations in the design of optimal products (Carroll and Green 1997).

Technically speaking, multidimensional scaling (MDS) uses similarity or dissimilarity values (also referred to as *proximities*) between all pairs of stimuli involved in a study as input, and permits an effective graphic presentation of perception data by projecting the stimuli in a multidimensional space, or spatial map (Borg and Groenen 1997; Dillon and Goldstein 1984; Schiffman, Reynolds, Young 1981; Kruskal and Wish 1978; Shepard 1972).

Similarly, in marketing applications, consumers' perceptions of similarity are represented in a multidimensional space where similarity is assumed to be inversely related to the distance between the relevant stimuli (Carroll and Green 1997). Indeed, the perceived relationships among the objects are deduced from the proximity ratings collected from the sample of respondents (SAS Institute Inc. 1997; Dillon and Goldstein 1984; Stefflre

1972) where the proximity data are regarded as an empirical measure of closeness between all pairs of stimuli (Green and Carmone 1970; D'Andrade et al. 1972). In other words, as the distance between two stimuli increases in the representational space, the perceived degree of similarity between the two decreases.

Hence, the stimuli that are perceived to be more similar are represented as closer. Such representation of the geometrical relations between the objects permits the extraction of the salient attributes used in their evaluation by the consumers (Shepard 1972) and therefore the underlying dimensions that would significantly capture the data (Borg and Groenen 1997). Those attributes that highlighted by the depiction of the stimuli in a dimensional space therefore presume the existence of a dimensional cognitive representation in consumers' minds (Johnson and Puto 1987), which is usually not even accessible by the individual himself.

2.2. Multidimensional Scaling (MDS) and Representation of Preferences

Just as in the representation of perceptions of similarity, a set of models and related software have been developed in MDS to model preferences (Carroll 1972; Carroll and Green 1997; Borg and Groenen 1997; Schiffman, Reynolds and Young 1981). Many of these approaches can be classified according to (1) whether they are vector or ideal point preference models and (2) whether the related analysis is an "internal" or "external" analysis of preferences (Carroll 1972; Green and Rao 1972; Green and Wind 1973; Kuhfeld 2004; Malhotra 1996).

The vector model of preferences (Carroll 1972; Schiffman, Reynolds and Young 1981, p. 256) attempts to find a direction through a multidimensional stimulus space which is the direction that corresponds to increasing degrees of preference. The model assumes that the stimulus space has already been determined by an MDS approach. Only the direction of the vector that represents the preferences of each subject or each group of subjects is to be determined. The orthogonal projections of the stimuli onto the vector of preferences represent how much each stimulus is preferred and preferences increase along the direction indicated by the vector. The vector model of preferences assumes that more is preferred to less. The ideal point model of preferences, however, assumes a "… hypothetical stimulus which, if it existed, the subject would prefer the most." (Schiffman et al. 1981, p. 259). These ideal points and the stimuli are represented in the same multidimensional space and those stimuli that are closer to the ideal point of the subject (or group) are preferred to the more distant stimuli. The distances between each stimulus and the ideal point are often used to predict consumers' product choices (Green and Srinivasan 1978; Lefkoff-Hagius and Mason 1993). As underlined by Carroll (1972) (see also Schiffman et al. 1981, p. 262), the vector model of preferences is a special case of the ideal point model where the ideal point is moved to the periphery of the multidimensional stimulus space. Vector model is recommended for stimuli where the researcher can assume that the utility of each stimulus increases if it possesses more of the related attributes (properties). The ideal point model, however, is suggested for stimuli where subjects have ideal levels of the underlying attributes in mind (for example, sugar level, a preferred level of loudness or hot sauce, etc) and the utility of each stimulus falls off in along all dimensions as the stimulus deviates from the ideal.

Preference models are also classified according to whether the related analysis is "internal" or "external" to the multidimensional stimulus space. In "internal" analysis of preference data, the joint space of configurations of stimulus points and ideal points representing subjects (or vectors of preferences for different subjects) is developed from preference data (Green and Rao 1972). The researcher primarily works with the data on overall preferences typically associated with N subjects and n stimuli. The outcome is a joint multidimensional representation of stimuli points and subject points (or vectors). That is, the coordinates of the stimuli as well as the ideal points or vectors are strictly derived from preference data. Carroll and Chang's MDPREF algorithm (Chang and Carroll 1969; Green and Wind 1973, p. 376) and Kruskal's M-D-SCAL program (Green and Wind 1973, p. 301) are widely known examples of vector and ideal point preference models, respectively, based on internal analysis. Other models and related algorithm references can be found in Carroll and Green (1997), Borg and Groenen (1997), Green and Wind (1973).

In "external" analysis, the researcher has a stimulus configuration in a multidimensional space that is obtained from some source (for example, MDS of similarity data) that is external to the preference data. The preference data are fitted into this stimulus space found from prior analyses of similarity data obtained from the same subjects for the same set of stimuli (Green and Rao 1972, p. 104; Green and Wind 1973, p. 101; Malhotra 1996). Carroll (1972) and Carroll and Chang have developed PREFMAP (Green and Wind 1973, p. 329), a versatile program for performing external analysis of preference data and representing stimuli as points and judges as vectors or ideal points.

2.3. MDS and Joint Representation of Perceptions of Similarity and Preferences

Earlier work in MDS modeled perceptions and preferences separately and proceeded with data analysis in parallel fashion obtaining perceptual spaces for each, or obtained a perceptual space based on an analysis of the similarity data and mapped preference ratings into the perceptual space through external analysis of preferences in a serial fashion. Beginning with the groundbreaking work of Ramsay (1980; 1991), however, it became apparent that a joint analysis of similarity and preference data (and possibly other rating data involving evaluations of objects along specified attributes) have clear advantages over earlier approaches. From a statistical point of view, the joint rather than separate analysis of various batteries of data sets (DeSarbo and Wu 2001) increases the reliability of the derived spatial maps and reduces the variance associated with the representation of points in the same spatial map (Ramsay 1980). Also, all available information is used simultaneously (Ramsay 1980). From a theoretical point of view, the joint analysis integrates various theoretically important constructs (perceptions, preferences, and additional evaluations of the relevant stimuli) into a single framework (Carroll and Green 1997). In their review of the psychometrics methods in marketing, Carroll and Green (1997, p. 199) suggest that the direction of future research includes a class of sophisticated models that involves the joint analysis of similarities, preferences and other relevant data.

The integrated approach in joint analysis derives a common perceptual space that simultaneously accounts for perceptual (e.g. similarity) and preference data and possibly additional ratings data in terms of a single geometric representation (Carroll and Green

1997, p. 198). MacKay and Zinnes (1995) discuss a probabilistic MDS model that allows for joint fitting of both proximity data and preference ratio judgements. DeSarbo and Wu (2001) extend the joint analysis framework and suggest a latent structure MDS procedure that can represent the common structure in preferences, dissimilarities and attribute information in the same spatial map and also account for segmented markets and consumer heterogeneity.

2.4. Similarity of the Dimensional Structure Underlying Perception and Preference Judgements

The joint analysis approach, although both theoretically and statistically promising, may involve the critical assumption that the dimensions of the spatial map underlying the perceptions of similarity and the preferences are the same. Furthermore, the configuration of stimuli under study, that is the coordinates of the brands, products, places, etc. may be assumed to be common in the model.

While these assumptions may be crudely summarized as "similar products are liked similarly", empirical evidence supporting these assumptions is not abundant and somewhat mixed (DeSarbo and Wu 2001). A study conducted by Lefkoff-Hagius and Mason (1993) revealed that consumers, in many occasions, considered *different* attributes when evaluating the similarity of various stimuli, and when expressing their preferences for the same stimuli. Wish (1971), with a study on countries, Lonial and Van Auken (1982) with a study on colors and cars, and Whipple (1976) with a study on mothers' judgements of toys, obtain similar results and conclude that it is unsafe to presume that product liking is consistent with product similarity, leading to the conclusion that the stimuli that are perceived to be similar are not necessarily equally preferred. On the other hand, MacKay et al. (1995) found *similar* cognitive structures for perception and preference judgements made over different gift items. Ramsay (1980) also found that model fit improved when preferences and perceptions (as well as other ratings) were considered jointly in estimation. DeSarbo and Wu (2001) also obtained good fit in a study of students' perceptions, preferences and attribute ratings associated with various brands in the soft drink market. MacKay et al. (1995), however, recognize that these promising results for the joint analysis of preferences and perceptions may not hold in all contexts and argue that the stimuli judged by the subjects when making perception judgements may be cognitively different, in certain situations, than those judged when making preference judgements, reflecting different cognitive spaces.

Besides the nature of the dimensions used by the respondents to form their perception and preference judgements, the importance granted to these dimensions was revealed to vary depending on the type of stimuli. Thus, another series of research examining soft drinks (Shocker et al. 1990 cited in Lefkoff-Hagius and Mason 1993) demonstrated that different weights were given to the same dimensions depending on the type of judgement made by the respondents (preference or perception judgements). Lonial and Van Auken (1982) make the same point and mention in their article that for the most part, research has so far revealed that perceptual and preferential criteria are the same and that only the saliency of dimensions is different.

2.5. Objectives of the Current Study

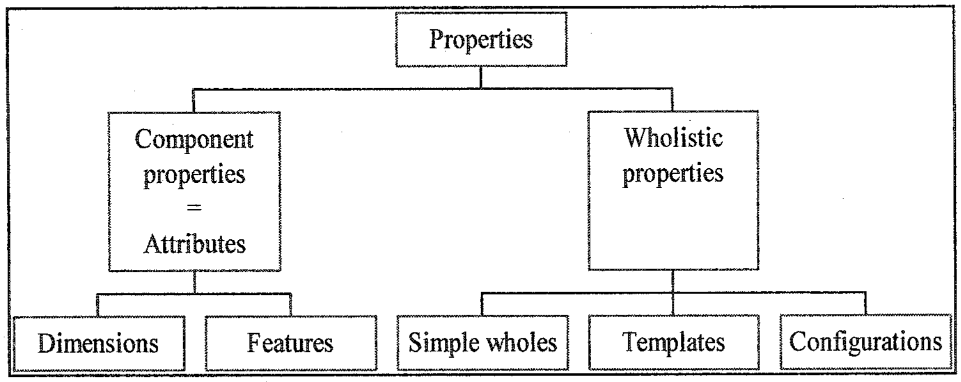
Given the reviewed mixed results, this research attempts to empirically test whether the assumption of common dimensions and common configuration of stimuli (that is, stimuli coordinates) are tenable for three different sets of marketing related stimuli that were selected after a careful review of the literature regarding the meaning of dimensions in MDS. The next section deals with a review of the conceptualization of attributes, features, and dimensions in psychology and marketing. The focal point of the review is what a dimension means in MDS and how dimensions differ from attributes, features, and characteristics to which marketing researchers have referred to describe various kinds of marketing related objects and stimuli. This distinction is later used to select the kind of stimuli for which the assumption of common dimensions and common stimuli positions in a joint spatial map might be true.

2.6. Attributes, Features and Dimensions

The multidimensional spatial map that we have been referring to previously can be compared to a Cartesian space with two or more coordinate axes which, in MDS terminology, are referred to as "dimensions". Hence, an n-dimensional space representation would have n axes, each axis representing a specific property that is taken into account by the respondents when they are evaluating and forming their judgements about the stimuli in a set. The greater the complexity of the data, the larger will be the number of dimensions required by the model to capture enough and allow a meaningful interpretation of the judgement process of the respondents (Shepard 1972). Objects are represented in this Cartesian space with corresponding coordinate values for the dimensions (axes).

A very important characteristic of these dimensions is that the properties that they represent are not dichotomous: each stimulus can present (or possess) each property (characteristic) to a certain degree (Johnson and Fornell 1987) and it is therefore possible to position all stimuli on the continuum of each dimension. In one of the original discussion on the kind of stimuli for which the dimensional representation is appropriate, Shepard (1972) underlines the requirement of a natural underlying continuum along which the objects of interest can be differentiated as a criterion for deciding the kinds of stimuli that can be used in MDS studies. Judgements involving sounds, colors (Shepard 1972), areas, and clarity of pictures (Ramsay 1980) are some examples of stimuli that can successfully be captured by continuous dimensions, whereas discrete features are more likely to be used for stimuli such as occupations or animals (Johnson and Puto 1987). As reviewed below, some researchers argue that the more abstract the attributes, the more appropriate is the conceptualization of the property of interest as a dimension (Johnson and Fornell 1987). Shepard's (1972) original point is that if the stimuli of interest are "naturally" positioned on each of various continua depending on the degree to which they possess the relevant property of interest, MDS is appropriate irrespective of the abstractness of the underlying attributes.

Figure 1: Garner's Categorization of Properties of Objects (1978)



In fact, one of the simplest and clearest ways to distinguish dimensions from features, which are often used interchangeably in the literature, was proposed by Garner (1978) (See Figure 1). He suggested that all stimuli have properties which can be divided into two distinct subcategories: component properties (also called attributes) and wholistic properties. While for the purpose of our study we will not get into details associated with wholistic properties, it is crucial in the current context to differentiate dimensions and features.

Garner (1978) suggests that the "concept of zero" is a critical criterion to conceptually separate dimensions and features. Simply put, zero is an indicator of the existence or absence of *features* in the evaluation of a stimulus. Hence, a feature is either observed as an attribute (or property) of a stimulus or it is absent (Garner 1978; Johnson and Fornell 1987). If the feature does exist, it has only a single level. As an example, a computer may or may not have a CD writer, but the existence of that attribute does not affect the fact that the object remains a computer. In this case, the CD writer is therefore a feature. Garner (1978) argues that it is always feasible to know the full range of potential dimensions that may exist in a stimulus, whereas it is possible to know all potential features if and only if all features exist in that stimulus.

On the other hand, and of greater interest for our study since multidimensional scaling (MDS) represents dimensions, zero takes another meaning within the *dimension* concept. It is here in fact as a positive value as any other degree on a continuum, or a value that a variable can take depending on its degree of "availability" in a stimulus (Garner 1978; Johnson and Fornell 1987). For example, a stimulus like a fabric may be very soft (high value on the softness dimension) or present no softness at all an even be rough to the touch (zero on the softness dimension). Zero, in the case of dimensions, is therefore one of the possible mutually exclusive levels on the dimension. Furthermore, a dimension cannot be removed from the stimulus without seriously compromising the existence of that stimulus. In our computer example, if we remove all memory from the computer, the computer ceases to be functional; properly speaking, it is not a computer anymore since it needs to have a certain level of memory to be operational. Hence, one should first ask him/herself if the dimension exists for the stimulus under study, and if the answer is positive, then determine the level at which it exists (Garner 1978).

The notions of concreteness and abstractness of attributes that was briefly mentioned above are also expected to play a critical role in the definition of dimensions. For example, Johnson and Fornell's (1987) experiments confirmed the hypothesis that as product representations become more abstract, the use of continuous dimensions as opposed to dichotomous features increased. Continuous dimensions would thus be more likely to be used to represent perceptual stimuli such as colors or tones (Shepard 1974), while features are expected to better describe conceptual stimuli such as occupations or animals (Johnson and Puto 1987). Basically, what the authors argue is that abstract attributes capture several more concrete attributes. Similarly, they suggest that one dimension may capture information about several features while the opposite is less likely to be accurate. Therefore, it would be reasonable to expect a relationship between the concreteness-abstractness properties of attributes and the use of features or dimensions; more concrete attributes having more chances to be represented as features, and more abstract attributes as dimensions because of their complexity (Johnson and Fornell 1987; Johnson and Puto 1987).

Since MDS is a technique that permits extraction of dimensions from respondents' perception and preference judgements, researchers must be certain, when dealing with MDS, that their respondents' judgements are based on dimensions as opposed to features (Johnson and Puto 1987). The stimuli set should therefore be selected accordingly. This is why the proper selection and definition of the stimulus set before data collection and analysis are so crucial.

3. HYPOTHESES AND RATIONALE

The reviewed literature suggests that the representation of stimuli along dimensions as it is done in MDS is appropriate mainly under two conditions: (1) the nature of the set of objects about which the subject expresses judgements forces the subject to use abstract continuous attributes rather than concrete features (that is, the objects are comparable only if high level abstract attributes are used) or (2) there are "*natural*" and continuous properties of interest along which the stimuli are differentiated irrespective of the level of abstraction. These two requirements constitute the theoretical foundation for the hypotheses of the current study.

The literature on consumer choice behaviour offers clues as to whether abstract continuous dimensions or concrete features are likely to be used in a particular comparison and choice context. Howard (1977) and Johnson and Fornell (1987) argue that each consumer choice belongs to a specific level in a choice hierarchy, where higher level choices involve choices across *product categories* (for example, choosing a birthday gift given a set of various products (MacKay et al. 1995)) and lower level choices involve choices among brands in a product class or various models of a particular brand. While feature-based comparisons are possible at the lower levels of the choice hierarchy, the stimuli become non-comparable in terms of features as the individual moves up in the hierarchy since the set of alternatives do not have common features (for example, consider buying a pen versus a sweater as a gift). Thus, the individual is forced to use abstract higher level dimensions along which the alternatives can be judged (Johnson 1984). Howard (1977) also suggests that more abstract attributes (dimensions) play a greater role in the decision process associated with product categories, while more concrete attributes (features) are given greater importance in brand-level choices. Also, during the decision process, as the choice set is narrowed down by eliminating unacceptable alternative the set of remaining alternatives may be homogeneous and the consumer's attention may shift to differences on specific features of the stimuli (Johnson and Puto 1987).

Given this theoretical background, the following hypotheses are formulated:

H1: Irrespective of the position along the choice hierarchy, the consumers are expected to use the continuous dimensions that naturally define a set of stimuli along various continua in their judgements. Therefore, the dimensional structure and the positions of the given set of stimuli for perceptions of similarity and preference judgements *will be similar* across the two spatial maps to be obtained for perceptions and preferences.

H2: For a stimuli set that is *high* in the choice hierarchy (that is, objects that can not be directly compared in terms of features), the consumers are expected to use abstract continuous dimensions. Therefore, the dimensional structure and the positions of the given set of stimuli for perceptions of similarity and preference judgements *will be similar* across the two spatial maps to be obtained for perceptions and preferences.

H3: For a stimuli set that is *low* in the choice hierarchy (that is, objects that can be directly compared in terms of features), the consumers are expected to use features of the objects, and therefore, the dimensional structure and the positions of the given set of stimuli for perceptions of similarity and preference judgements *will be different* across the two spatial maps to be obtained for perceptions and preferences.

4. METHODOLOGY

4.1. Construction of the Research Instrument

4.1.1. Choice of Stimuli Sets

Each of the three hypotheses mentioned in the previous section was tested in a separate study. Hypothesis 1 involves a set of stimuli that are naturally defined along multiple continuous dimensions. For example, Shepard (1974) suggested that continuous dimensions would be more likely to be used to represent perceptual stimuli such as colors or tones. Hypotheses 2 and 3 involve stimuli sets that are either high or low, respectively, in the choice hierarchy. If the stimuli are high in the choice hierarchy, the consumers are expected to use abstract continuous dimensions in their judgements. If, however, the stimuli are low in the choice hierarchy, the objects are directly compared in terms of their features rather than a common dimensional structure. Thus, three separate stimuli sets were defined so that the objects followed the related characteristics mentioned in the hypotheses.

Several criteria mentioned in the literature were also observed during the selection process of our stimuli: we chose objects for which the subjects were relatively homogeneous in their knowledge and familiarity, and we also opted for simple stimuli that could be described with relatively few attributes (Lefkoff-Hagius and Mason 1993). We also made sure that the objects selected in each stimulus type were comparable to one another given a specific use context, since multidimensional scaling is known to provide the most consistent results when the stimuli belong to a single conceptual sphere (Nerlove and Romney 1972). The number of objects that could collectively represent a choice context was also an important element to consider since multidimensional scaling of perceptions typically involves $n\,(n\text{-}1)/2$ pairwise ratings for n stimuli, presenting too many stimuli leads to asking the respondents to make a large number of ratings which may become too demanding, while too little stimuli may result in unstable solutions (Dillon and Goldstein 1984).

Based on these criteria and the object characteristics specified in the related hypotheses, the type of stimuli to test H1 included "[…] domains of objects in which there is an underlying continuous *physical* variation […]" as suggested by Shepard (1974) and Johnson and Puto (1987). Shepard argues that even when the stimuli vary only in discrete steps, a representation within a continuous coordinate space is often satisfactory. We opted for **fabrics** to represent this category of stimuli, and conducted a tactile blind-test. Tactile sensation appeared to be the appropriate sense to test since the fatigue effect is less important than with smell or taste, for which it is usually necessary to wait several minutes between each stimulus in order to avoid any confounding effect. Such a wait increases data collection time and reduces subject cooperation. Therefore, opting for fabrics made the data collection step much shorter and more realistic than taste and smell tests.

The second hypothesis required a set of objects that were not directly comparable but comparable only through *abstract* (Johnson 1984) and *possibly continuous* dimensions (Johnson and Fornell 1987). In other words, the second category of stimuli was made up of nominally different or non-comparable objects that could still be evoked as alternatives in the same usage context. In this case, we opted for the comparison of **transportation modes** (such as car, bus, taxicab, bicycle, etc.).

The third hypothesis required objects that would be low in the choice hierarchy (that is, objects that *can* be directly compared in terms of discrete features). A possible context for such a set of objects is the comparison of various brands in a category where the brands have clear and distinct features, the features vary across brands, and the comparison involves mainly an observation of the existence and absence of certain features by the objects. Considering the sample of respondents that we were targeting (university students), **brands of cereals** such as Müslix, Corn Flakes, Cheerios, etc., appeared to represent a good option that met the criteria for selection mentioned above.

4.1.2. Developing Scenarios to Specify Situational Context

Previous research in consumer behaviour clearly shows that subject heterogeneity in perceptions and preferences is a function of use situation (Belk 1975; Lonial and Van Auken 1982). As pointed out by Ratneshwar and Shocker (1991), consumers evaluate products or stimuli as "[…] means to achieving the ends inherent to the usage contexts […]". As the use situation varies, a variation is expected in perceptions and preferences. Also, when the same stimuli are given to a group of subjects in a test situation, it is possible for them to assume different use or situation contexts, which in turn may create heterogeneity across subjects in terms of perceptions and preferences.

In order to avoid such potential subject heterogeneity, a use or choice context was specified for each set of stimuli in studies 1 through 3 as presented in Appendices 1.1, 12. and 1.3. In Study 1 dealing with tactile information search involving fabrics, the subjects were instructed to consider a set of fabrics as a possible blouse to be worn at a graduation party to take place at a five-star hotel mid June. They were asked to look for a special and comfortable fabric for the occasion. In Study 2 dealing with various transportation modes, the subjects were instructed to assume that they live in an apartment/house that is located at about five kilometers from their school that was situated downtown in a metropolitan area. They were asked to consider several transportation options for the month of September. Finally, in Study 3 involving cereals, the subjects were asked to evaluate a set of various brands of cereals to be consumed on a cold January day before heading up North for a full weekend of sport activities (skiing, skating, or hiking) with friends. The subjects were told that they had a demanding weekend ahead and a two-hour drive. Please see Appendices 1.1 through 1.3 for the exact wording of the use situations.

When developing the three scenarios, special attention was taken to provide realistic and interesting scenarios that could be appropriate for both male and female students. For the fabric experiment, however, the described situation (blouse for graduation party) required that the subjects of first study to be limited to females.

4.1.3. Final Selection of the Stimuli and Pre-tests

First, for the fabric experiment, after having ourselves tried to distinguish the features of samples of fabrics collected from a regular textile retail store through the lens of a microscope, we realized that the complexity of the components (fibber thickness, number of fibbers in a yarn, density of the fabric, threading method, etc.) was overwhelming and that the assistance of a specialist in that field was a necessity. We therefore relied on the expertise of a manager in charge of research and development at a major multinational Canadian textile company to select nine fabrics to include in our study. In summary, we were looking for fabrics that perceptibly varied along two main dimensions (thickness and softness). We deliberately selected fabrics that varied greatly along these two dimensions given our scenario (blouse for a graduation party in a five-star hotel reception room) in order to maximize the probability that our respondents' perceptions and preferences would vary in a homogenous manner. Finally, extra precautions were taken by selecting 100% polyester fabrics only in order to eliminate the effect of some potential binary features that would not have been captured by MDS such as the type of fibber (cotton, polyester, nylon, etc.). Guided by the textile expert who helped us in the selection process of the nine fabrics, we positioned all stimuli in a two-dimensional grid, in terms of their thickness and softness with regards to each other. An approximate version of that grid as well as a comparative table including the finished weight of each fabric selected, which can be used as one but not the only indicator of the thickness of the stimuli, are available in Appendix 3.

We then conducted a pre-test with five respondents for the fabric experiment to see if the use of nine fabrics for that one-on-one blind-test experiment was realistic and feasible or if it was too time consuming. When the number of stimuli is large and the task too demanding, MacKay et al. (1995) suggest to reduce the experimental load by using incomplete sets of pairwise comparisons. Fortunately, our pre-test revealed that the task was doable with nine stimuli and we therefore concluded that we could proceed with the experiment without modifying the questionnaire.

No pre-tests were conducted for the transportation modes experiment, but several persons were involved in the brainstorming sessions preceding the final selection of the stimuli and we assumed that all respondents were familiar with all transportation modes. No pictures of the stimuli were provided for this experiment, but all stimulus names were printed on an extra sheet, which was next to the respondents and available for them to refer to through out their task. This measure was taken to encourage them to keep all stimuli in mind while filling out the survey, which they may have been less likely to do if the stimuli had been available on the cover page of the questionnaire only.

Finally, a pre-test taking the form of a recall task was conducted for the study involving various brands of cereals. An email was sent asking 19 respondents (10 females and 9 males, all between the age of 20 and 26 years old, students or graduates within the last two years to provide the name of all the brands of cereals that they could spontaneously recall without aid and with which they were familiar. We compiled the results and a total of 39 brands were evoked by our subjects. We therefore selected and used the nine brands that were the most frequently mentioned in the pre-test to build the final survey. These respondents who participated in the pilot experiment were not allowed to participate in any of the three studies.

A color copy of the logos of these nine brands of cereals was later provided to the respondents of the third study during the data collection sessions in order to eliminate any confusion between brands. Precautions were however taken to delete all pictures of the cereals themselves in order to ensure that the subjects' judgements were entirely based on their recall of the brands. A copy of the pictures of the logos presented to the participants is available in Appendix 2.

4.1.4. Assessing Respondents' Perceptions and Preferences

Because we wanted to assess consumers' perceptions and preferences, we divided our questionnaire into two main sections, which were preceded by a brief introduction giving information and instructions, and the use/situation scenario. The instructions clearly asked the respondents to keep the scenario, and therefore the use-context, in mind throughout the survey. Please see Appendices 1.1, 1.2, and 1.3 for the questionnaires.

The first part of the survey required the respondents to evaluate the similarity level between the stimuli. This can usually be accomplished by two main methods: either from *deriving* the proximity information from scores associated with each stimuli involved in the study (e.g., ratings of the objects on descriptors or adjectives), or by asking the subjects to *directly* rate on a similarity basis all possible pairs of objects of the stimuli set (Borg and Groenen 1997, Dillon and Goldstein 1984). The second method described was retained for our study. Indeed, using pairwise ratings presents several advantages such as the development of indexes that provide information on the quality of the ratings provided by the participants. Hence, pairwise ratings "[…] can be reduced to scale values for each stimulus and, in the process, an internal consistency index can be computed [...]" (Ramsay 1980). The researcher to evaluate the quality of the results provided by the subjects can then use this internal consistency index. Poor quality may be attributable to several factors; it can be due to difficulty with the rating task but also to low involvement in the assignment. It is always beneficial to have an index that permits the identification and the elimination of such respondents.

While there exists a variety of ways to collect similarity data, we opted for "line marking". The respondents' task was thus fairly simple and straightforward; given the use context described by the scenario, they were asked to project their similarity judgements by drawing an "X" on an undivided scale ranging from 0 (very dissimilar) to 100 (very similar). The more the perceived similarity, the higher on the scale their ratings were therefore expected to be. If this type of data collection method for distance judgements is perceived as highly inconvenient at the data coding stage by several authors (because each subject's responses has to be measured using a ruler), we felt that it would nonetheless allow us to obtain more spontaneous judgements from our respondents, and that their ratings would reflect in a more accurate way and with more precision their perceptions and preferences for the stimuli (e.g., if a pair of stimuli is perceived to be only very slightly different from another one, the marks on the lines should be very close, perhaps closer than if the subjects were asked to rate the pairs by circling numbers on the line, as in category ratings).

Very importantly, the subjects were not given any hint on what basis to judge the pairwise similarity since the purpose of MDS is specifically to highlight the dimensions underlying these judgements (Stefflre 1972).

The pairs of stimuli were presented in a random fashion and a table suggested by Ross (1934) was used to create the order of presentation of the pairs. This table permits the elaboration of the optimum order for the presentation of pairs in pair comparison tasks, and hence insures us that risks of position (left vs. right) and timing errors (e.g., always having the same stimulus in first position in the pair) and repetitions which might also influence judgement were minimized, and that the greatest possible spacing between pairs in sequential presentation was maintained.

In the second part of the survey, the *preference* condition, subjects were invited to specify how much they liked each stimulus on a rating scale ranging from 0 (dislike very much) to 100 (like very much). They were then asked to go over their preference judgements again and to think about how much they liked each stimulus versus the others. They were encouraged to modify any ratings to reflect their relative preferences. These last instructions were given because previous studies demonstrated that subjects often find preference judgements easier to make when they can explicitly compare their ratings as opposed comparing stimuli with an implicit standard which can change from time to time or from subject to subject (Ramsay 1980).

The second part of the questionnaire also included a last sub-section requiring the respondents to rate, again on an undivided scale that ranged from 0 to 10, *each stimulus* along three attributes that we believed would be found to be the main dimensions or that would at least aid in the interpretation of the dimensions later obtained in the perceptual map. As an example, the three attributes on which each fabric was rated were "thickness", "softness" and "comfort". The attributes for the transportation mode study were "time consuming", "expensiveness", and "degree of physical effort needed". For the study on brands of cereals, the three attributes were "degree to which the cereal is filling", "healthiness" and "how much energy the cereal provides". Again, the participants were asked to review their ratings across all stimuli and modify any ratings to express their relative judgements better.

When brought back by the participants and before granting the monetary compensations, all questionnaires were verified by the researcher in charge of the data collection sessions to insure that there were no missing data.

4.2. Sample of Persons to be Studied

All stimuli were chosen considering the sample that we were going to study. We insisted on the need to have a sample of participants belonging as much as possible to a single market segment, which is defined as a group of consumers who evaluate objects or marketing appeals differently from other clusters of buyers (Green and Carmone 1972). Given the objectives of our studies, our decision to target a single market segment relied on the intention to maximize the likelihood that participants' judgements would be fairly homogeneous. The sample of respondents to be included in this study was however a convenience one, constituted of university level students (graduates and undergraduates) from both genders, except for the fabric experiment for the reasons that we mentioned earlier. Since the objectives of the study do not involve generalization of the results to a wider population of consumers, this sample was considered to be acceptable.

Even if, as described above, we took some measures to reduce the likelihood of obtaining heterogeneous judgements across the participants, there is empirical evidence that preference and perception judgements are indeed subjective and may be heterogeneous across consumers (Shocker and Srinivasan 1979, cited in Lefkoff-Hagius and Mason 1993). For that reason it was important to design a study in which both perception and preference judgements would be provided by the same respondents. Therefore, a within-subject design was used, requiring the participants to evaluate the same set of stimuli in terms of perceived similarity and preferences. A between-subject design was however more appropriate regarding the evaluation of the three types of stimuli (the respondents did not participate in all three studies) since the rating task required by each questionnaire was a demanding and time consuming one and therefore it would not be realistic to expect a given subject to provide data for all three studies. Therefore, a recruited subject filled out only one of the questionnaires given in Appendices 1.1, 1.2 and 1.3.

Finally, data were collected from 50 respondents for each of the three experiments, resulting in a total sample size of 150 participants. Similar sample sizes of about 50 have been reported in the literature (Mackay et. al. 1995; DeSarbo and Wu 2001) for joint analysis of preferences and perceptions.

4.3. Data Collection

The data were collected in multiple sessions for each study on the Concordia University campus (both Loyola and downtown campuses) in Montreal at the end of November 2003. A booth with a sign announcing the study and the monetary compensations was set up in two different high traffic locations on the two campuses and the subjects were actively recruited.

For the brands of cereals and the transportation modes questionnaires a filter question was used to insure that all respondents were familiar with all stimuli of the study in which they were involved. Indeed, intuitively and as it has been suggested by other researchers, unfamiliarity with the stimuli is likely to affect similarity judgements (MacKay and Zinnes 1986; Johnson et al. 1992, all cited in Bijmolt et al. 1998; Davison 1983). The subjects who met the requirement of familiarity were then asked to have a seat directly at the booth, most of the time several respondents at a time (except for the fabric experiment), and filled the questionnaire in the presence of the investigator. This measure appeared important to us to ensure that the subjects could ask any question if they felt the need to do so, and to exercise some control to make certain that they were not rushing through the survey. This last concern was also addressed by asking the participants to wait for further instructions between each section of the questionnaire, until they were told to proceed.

Each data collection session started with a welcome statement. The subjects were then asked to sign a consent form, informing them of their rights as participants in a research, acknowledging their agreement to participate in the study. Next, the subjects were supplied with a questionnaire and were instructed to pay attention to the stimuli of the study that were presented to them prior to data collection. It was hoped that this initial stage of familiarization with the complete set of stimuli would help the subjects establish a frame of reference for their judgements.

The first study that involved the tactile information search on fabrics presented each pair of fabrics as four inches by four inches samples on a page of a booklet behind a curtain suspended from a frame. As the subjects touched each pair of samples and expressed their judgements, the pages of the booklet were turned by the investigator. In the preferences section and also the section where each fabric was rated along one of three attributes ("thickness", "softness" and "comfort"), a different booklet presenting each fabric as a separate sample was used. When the subject completed a section (say, ratings of fabrics along "thickness"), the investigator turned back to the first page of the booklet to let the subject rate the fabrics in terms of "softness" and so on.

It took between 15 and 20 minutes for each respondent to complete the questionnaire on transportation modes and brands of cereals. The fabrics experiment required a bit more time (between 20 and 30 minutes per respondent) because the blind-test task was obviously more time consuming. All data were collected in about two weeks. Subjects were exposed to only one of the three stimuli sets and were not allowed to participate in more than one experiment (between-subject study) and were not told the purpose of the experiment (but had the option to leave their email address to receive additional information on the purpose of the study if they wished).

Monetary compensations were distributed to the respondents ($7 for brands of cereals and transportation modes, and $10 for fabrics since the task was more demanding and more time consuming). The attribution of these compensations served three purposes: first, it was a means to encourage people to participate in the study, second, it appeared important to us to thank the participants for their time, and third, we thought that this measure would encourage the subjects to give honest answers and to fill out the survey seriously (feeling of responsibility toward the task since they were getting paid for it).

5. DATA ANALYSIS AND FINDINGS

5.1. Data Coding

Once the data collection sessions that are described in the previous chapter were completed, we coded all data (similarity judgements, preferences, and attribute ratings) by measuring with a ruler the distance between the left end of the scale and the "X's" put by the respondents on the lines. We then converted these measures into ratios by dividing the measures obtained, by the total length of the line, and by multiplying these results by 100. Therefore, for the similarity judgements for instance, the percentages obtained were ranging from 0%, indicating "very dissimilar", to 100%, indicating "very similar". These ratios became our observed scale values to be used as input in our data analysis.

5.2. Data Pre-Processing

5.2.1. Building Symmetric Similarity Matrices for all Three Experiments

Once all ratings were converted to percentages, the usable measures associated with the perception judgements (the similarity ratings) were put into a similarity matrix form, with rows and columns corresponding to the nine stimuli involved in each specific study. A similarity matrix, also named a proximity matrix, is a way of organizing the data describing the closeness between all pairs of stimuli (Green and Carmone 1970). In these types of matrices, it is assumed that the more similar the stimuli are, the larger their corresponding value is (the closer it is to 100%).

The type of matrix used was a symmetric one, meaning that we had zeros on the diagonal and that the upper and lower triangles of the matrix were reflections of one another. An example of the type of symmetric similarity matrices used is available in Appendix 4. As it can be observed in this example of symmetric similarity matrix for subject 1, the numbers associated with all pairs of stimuli are in fact percentages representing the perception ratings of this respondent for all pairs of transportation modes. Hence, for this participant, the two most similar transportation modes are "metro" and "bus" with a similarity rating of 86.022%, whereas the two most dissimilar stimuli are "walk" and "bus" with a similarity percentage of 16.129%.

These matrices were built for all respondents and for all stimuli sets involved in our study, and were later used in various MDS analyses.

5.2.2. Attribute Ratings

As we mentioned earlier in the methodology section, the participants were invited to rate each stimulus involved in the study on three attributes that would later be used to label (names) the underlying dimensions of perceptions and preferences resulting from the MDS analysis. A compilation of the mean values for the ratings on each attribute for each stimulus type (fabrics, transportation mode alternatives, and brands of cereals) as well as the bar graphs displaying the results and the correlation coefficients between the attribute ratings are available in Appendix 5. A close analysis of the means resulting from the ratings provided by our subjects reveals several interesting elements.

Hence, for the stimulus type corresponding to the stimuli set the highest in the choice hierarchy, the *fabrics*, we observe that two of the three attributes, namely "softness" and "comfort" are very closely linked as indicated by a correlation value of 0.995. Furthermore, for many fabrics, thickness is negatively correlated with softness (-0.789) and comfort (-0.804); for example, for the thickest fabric (labeled as "A"), we also observe the lowest levels of softness and comfort. Conversely, the fabric that is perceived to be the thinnest is also perceived to be one of the most comfortable and one of the softest. Finally, if we refer again to Appendix 3 and compare the ratings obtained from the participants with the objective ratings of the fabric stimuli, we conclude that the results provided by the measurement of the perceptions of our respondents on the three attributes mentioned above are monotonically related but not identical to the ratings of the nine fabric stimuli on the two attributes (thickness and softness) determined by the two researchers with the guidance of the expert textile engineer. As demonstrated in Table 1 of Appendix 5, strong correlations between the predicted and the observed coordinate values were nonetheless obtained for the thickness (0.905) and softness (0.848) dimensions.

If we move on to the stimuli set associated with the middle level of the choice hierarchy studied in this research, the *transportation mode alternatives*, we observe that the means are as expected: car and taxi cab being the most expensive transportation modes, and walking and riding a bicycle being those that require the most exercise. Some of the average values however seem to contradict expectations, for example, train being more time consuming than bicycle is one example. However, given the scenario that the subject is only five kilometers from his/her destination, bicycle may be perceived to take less time than taking the train to the same destination. The results nevertheless globally confirm prior expectations.

Lastly, the means across the nine *brands of cereals* show less variation than the means for the other two sets of stimuli. The means obtained for the most (Müslix) and least (Froot Loops) healthy brands seem to be representative of reality, as it also appears to be the case for the seven other brands in between. Overall, we can nonetheless conclude that the respondents had more difficulty than in the two other experiments to distinguish one brand of cereal from another in terms of the attributes mentioned. Overall, Frosted Flakes and Froot Loops seem to be clearly different than the other brands since they have relatively low average ratings on one or more of the three attributes.

5.3. Data Processing

Data analysis was conducted using the statistical procedures and market research related macros for graphical display available in SAS (SAS Institute Inc. 1997). Additional software such as Excel and S-Plus were also used for data pre-processing and preparing the input data for SAS and graphical displays.

A schematic flowchart available in Appendix 6 summarizes the overall data analysis steps that we went through for each of the three stimulus sets involved in this research. As noted in Appendix 6, data analysis proceeds by applying multidimensional scaling (SAS MDS procedure) to perceived similarity data and multidimensional preference analysis (SAS PRINQUAL procedure) to preference data. After determining the appropriate dimensions and obtaining the coordinate values for the stimuli set using the MDS and PRINQUAL procedures, the PRINQUAL solution is orthogonally rotated to maximum congruence with the MDS solution using the rotation method suggested by Cliff (1966), and the correlation coefficients for the coordinate values of the corresponding dimensions of the perception and preference related solutions are computed. High correlation value for each of the retained dimensions suggests similarity of the underlying dimensional structure for perceptions and preferences. Also, the data involving the three attributes for each set of stimuli are used for property fitting (PROFIT) to label the dimensions for the perceptions and preferences. The fitted properties (that is, the additional three attributes) should lead to similar interpretations of the underlying dimensions.

5.3.1. Metric and Nonmetric Multidimensional Scaling

Metric (or classical) multidimensional scaling and nonmetric multidimensional scaling (also referred to as the "Shepard-Kruskal" variety of MDS) are two classes of MDS procedures that were developed about ten years apart. The main difference between the two is that while metric MDS involves interval or ratio scaled data, nonmetric MDS involves data with only ordinal properties (Borg and Groenen 1997; Dillon and Goldstein 1984; Green and Carmone 1970). A conservative stand was taken in this study and it was assumed that the pairwise similarity perceptions and preference ratings were ordinal at best. For this reason, we opted for the use of nonmetric multidimensional scaling.

Nonmetric MDS was first developed by Shepard in 1962 (cited in Young 1972) in an attempt to extract the coordinates and the configuration of various stimuli as well as the distances between them based on their perceived similarity, and that, from nonmetric information (e.g., ordinal information) collected from a sample of respondents (Napior 1972). Only a few years later, Kruskal (cited in Young 1972) improved the algorithm introduced by Shepard by suggesting that each solution obtained from such method of analysis had the potential to be "perfect". The notion of "badness-of-fit" of a solution and the related measure of stress then introduced to reflect how close the input proximities (similarity data) or a function of them were represented by the distances computed from the estimated coordinate values for the related stimuli.

5.3.2. Analysis of Similarity Data at the Individual Level –Unweighted Multidimensional Scaling (MDS)

While the preliminary analysis of the averages associated with the attribute ratings revealed that a majority of the respondents seemed to have provided meaningful ratings of the stimuli sets, the next step of our data analysis was intended to obtain a global picture of the quality of the results provided by our sample. The objective of the data analysis at this stage was to identify and eliminate those subjects who may have supplied data with much error due to lower involvement with the tasks asked of them or those subjects for whom the spatial (geometric) representation of similarity judgements by MDS was not appropriate. To do so, we ran a simple or unweighted MDS analysis at the individual level (one subject at a time) using the SAS software for two, three, and four dimensions and estimated the badness-of-fit indices for each subject.

Multidimensional scaling analysis (MDS) among other elements permits the extraction of the distances between the stimuli involved in the experiment. In other words, it is possible to obtain from MDS plots of the stimuli objects reflecting the resemblance perceived by the sample of respondents for all these stimuli. In statistical terms, the Euclidean distance (distance between the objects in the multidimensional space), is an indicator of the similarity between two stimuli, let say stimulus *i* and stimulus *j*, that may be obtained by the following formula (Dillon and Goldstein 1984):

$$\overset{k}{d_{ij}} = \sqrt{\sum_{a=1}^{n} \left(x_{ia} - x_{ja}\right)^{2}}$$

Where $\overset{k}{d_{ij}}$ represents the distance between stimuli *i* and *j* for subject *k*, $\sum_{a=1}^{n}$ implies that the summation is over *a* dimensions, and finally x_{ia} *and* x_{ja} are row vectors expressing the coordinates of the two corresponding stimuli.

When performing MDS, the SAS MDS procedure by default expects distance or dissimilarity matrices, for which larger values refer to more *dissimilar* stimuli. Since we measured on 0 to 100 scales how *similar* the pairs of stimuli were perceived to be by the respondents, 100 corresponding to *very similar*, we specified in the statements that the input data were similarity matrices (SIM=100), where 100 indicates that the ratings were on one hundred.

We also indicated that the measurement level of our data was ordinal (LEVEL=ORDINAL) which means nonmetric MDS was performed, that the type of matrices involved were identity matrices (which yields Euclidean distances in unweighted MDS) (COEF=IDENDITY), that squares of distances be fitted (greater significance should be attributed to larger data and distances, and lesser significance to smaller data and distances in fitting the model) (FIT=SQUARED), and finally that the maximum number of iterations to perform in order to obtain convergence of the model was 200 (MAXITER=200). We then indicated that the formula to use to obtain the badness-of-fit criterion was Kruskal's *stress-1 formula* (FORMULA=1 which standardizes each partition by the uncorrected sum of squares of the data, unlike FORMULA=2 which uses corrected sum of squares), also mentioned below, and we asked the software to perform all these statements with two to four dimensions (DIMENSION=2 to 4) to allow comparisons of the output in various dimensions.

The badness-of-fit statistic that we referred to above, also called the "stress measure" and developed by Kruskal (cited in Dillon and Goldstein 1984 and in D'Andrade et al. 1972), is a useful statistic always ranging from 0.0 to 1.0 for which higher values indicate poorer fit, or in other words indicate that the subjects may have given almost random responses. This stress measure is given by the stress formula one (Dillon and Goldstein 1984; Davison 1983; Green and Rao 1972; Green and Carmone 1970):

$$S = \left[\frac{\sum_{i \neq j}^{n} (d_{ij} - \hat{d}_{ij})^2}{\sum_{i \neq j}^{n} d_{ij}^2} \right]^{1/2}$$

Where d_{ij} and $\hat{d}_{ij}$ respectively refer to the *distances* between stimuli *i* and *j* computed from the MDS solution involving the coordinate values for a given dimensionality, and to the *fitted distances* between *i* and *j*. $\hat{d}_{ij}$ are sometimes called "disparities" and they are simply transformations of the input proximities (similarities). Hence the numerator simply measures the fit of the distances computed from the MDS solution to the proper transformations of the input data. Thus, the closer the distances computed from the derived coordinate values is to the disparities, the closer to zero will be the numerator (and therefore the S value) indicating a better fit. In contrast, the denominator is here a normalizing value that allows the comparison of the badness-of-fit measure across different dimensionalities (Green and Carmone 1970). In this form, STRESS is analogous to $\sqrt{1-R^2}$ where R^2 is the multiple correlation coefficient in regression. Thus, STRESS is the square root of a normalized residual sum of squares (Kruskal and Wish 1978).

It is important to reiterate that the stress formula that was used in this research fitted *squares* of proximities to *squares* of distances, which makes the related fitting algorithm more sensitive to the larger rather than smaller distances. Therefore, the related terms above in the formula for stress *S* are replaced by $d_{ij}^{\;2}$ and $\hat{d}_{ij}^{\;2}$. This form of stress is actually what is called S-STRESS-1 in ALSCAL, a model and related fitting algorithm for MDS (Takane, Young and de Leeuw 1977; Young and Harris 1990).

As mentioned above, there also exists the STRESS-2 formula for which the denominator only is different ($\sum_{i \neq j}^{n} (\hat{d}_{ij} - \hat{d}_{..})^2$) but it is suggested that it should mainly be used for preference data while the first one is more appropriate for perception data (Davison 1983). Hence, STRESS-2 formula was dismissed in this analysis.

The unweighted MDS analyses were run individually for all subjects for each of the three stimuli sets involved in our studies. After 200 iterations, the related algorithm achieved convergence for all subjects. A STRESS-1 value was computed for each analysis for two, three, and four-dimensional solutions. Minimum, maximum, mean, values of the stress values for each study, and the variance and standard deviation of these stress values are presented in Table 1 of Appendix 7.

As it would be expected, the mean badness-of-fit statistic is inversely related to the number of dimensions; as the number of dimensions increases, the stress measure decreases, indicating that the overall configuration is better fitted by the model and therefore that the fit of the results is superior. For instance, in the fabric experiment, the mean stress measure dropped from 0.12 for two dimensions to 0.06 for three dimensions and to 0.03 for four dimensions. Drops in the fit indices of similar magnitudes can be observed for the transportation mode alternatives and for the brands of cereals stimuli as well. Furthermore, the respective standard deviation indices of the stress values also tend to decrease as the number of dimensions increases, meaning that the badness-of-fit measures for all respondents have a tendency to be closer to the mean in greater dimensionality (e.g., for fabrics, the standard deviation indices drop from 0.04 to 0.02 to 0.01 for two, three, and four dimensions respectively).

In many situations, the stress measure is one of the aids used to determine the minimum number of dimensions that should be considered by the researcher in MDS (Kruskal and Wish 1978). Since the stress measure tends to decrease as the number of dimensions increases, a plot of the stress measures against the number of dimensions may help to determine at what point it is not worthy to include an additional dimension (D'Andrade et al. 1972). At this stage of the analysis, we were not interested yet in determining the optimal number of dimensions to use. The focus of the analysis at this stage was to determine whether any subjects needed to be dropped from further analysis due to extremely poor fit. As Table 2 of Appendix 7 shows, for two, three, or four dimensions obtained with the unweighted MDS a vast majority of the respondents would be kept for cut-off STRESS values between 0.20 and 0.25. Indeed, when the number of dimensions was three or more, none of the subjects exhibited STRESS values exceeding 0.20. So, all subjects were retained for the next stage of data analysis.

5.3.3. Analysis of Similarity Data Using Weighted Multidimensional Scaling (MDS)

As Glazer (1984) indicates, an important body of work in psychology has revealed that perceptions can be biased, non-objective, very error-prone, and individual-specific. Hence, once we had confirmation that our subjects' involvement with the three MDS tasks that were presented to them seemed to be satisfying and that the data did not contain excessive error, the next step in data analysis focused on conducting a *weighted* multidimensional scaling analysis, also called *individual differences scaling* (INDSCAL) at the group level for each study.

Weighted MDS model was first introduced to the literature by Horan (1969) and Bloxom (1968), and was later further developed by Carroll and Chang (1970). The basic idea of the model is to capture the common (group) perceptions as well as the individual deviations from the common perceptions in terms of how each individual uses the dimensions underlying the common perceptions (Carroll and Chang 1970; Carroll and Green 1997; Dillon and Goldstein 1984; Kruskal and Wish 1978). Indeed, many studies have demonstrated that different individuals may form their perceptions based on a common set of dimensions but that the significance of these dimensions varies from one respondent to another with the possibility for it to have a "zero" importance, meaning that that specific dimension is not salient at all for some individuals (Carroll 1972). In other words, the important aspect of the of individual differences scaling (INDSCAL) model is that it assumes that subjects belonging to a homogeneous group will evaluate the same stimuli using a "psychological space" common to all respondents. However, each subject has an individual space that corresponds to a shrinkage or a stretch of the dimensions of the group space, reflecting individual differences.

Mathematically speaking, weighted MDS (or individual differences scaling –INDSCAL)[1] can be conceptualized by a formula linking the stimulus coordinates to the distances perceived by a particular participant and by attributing the appropriate dimension weight for that respondent (Wish et al. 1972; Carroll 1972). The formula used to assess the distance between two stimuli is therefore exactly the same as for unweighted MDS with the addition of a weighting factor (Dillon and Goldstein 1984):

$$\overset{k}{d_{ij}} = \sqrt{\sum_{a=1}^{n} w_{ka} \left(x_{ia} - x_{ja}\right)^{2}}$$

[1] Strictly speaking, the version of weighted MDS that is used in this study is not INDSCAL since the level of measurement is assumed to be ordinal while INDSCAL was originally developed for metric data.

Where w_{ka} is the weighting factor and can be thought of as the importance of the a^{th} dimension for the k^{th} subject. Interestingly, the square of the weighting factor of a participant on a specific dimension indicates the percentage of the variance in that subject's similarity data that can be accounted for by that dimension.

We ran a weighted MDS (INDSCAL) for two, three, and four dimensions with the similarity data associated with each of the three stimulus sets. The SAS MDS procedure was the same as the one used with the unweighted MDS except that the weights associated with each dimension for each subject were estimated (COEF=DIAGONAL), which now was needed to take into account the individual differences.

A summary of the results of this step of the analysis is presented in Appendix 8. As expected, stress values decrease as the number of dimensions increases. Also, the stress values are in general higher in weighted MDS than in unweighted MDS that was mentioned previously: the badness-of-fit average value for all types of stimuli and for all numbers of dimensions being 0.24 as compared with 0.07 for the unweighted MDS. This increase in the average stress values is to be expected since the unweighted MDS that was presented above was conducted at the individual level and distances were fit to data for each individual separately. The weighted MDS, however, assumes a common stimulus space for the whole group, and the freedom of fitting each data set for each individual is lost except for the individual differences that are captured by the dimensional weights. That part of the individual differences that are not captured by the dimensional weights increases the residual sums of squares in the numerator of the stress formula, increasing the stress value calculated for each subject and the average stress value for the whole group.

Table 2 of Appendix 8 presents the number of subjects that would be retained in further analysis if cut-off values of 0.20, 0.22, and 0.25 were used for two, three, and four-dimensional solutions. When the results are compared across the three kinds of stimuli, it is interesting to note that, for a given number of dimensions, the largest number of subjects would be retained for fabrics that were intentionally selected given rather continuous underlying dimensions of fabric thickness and softness. The smallest number of subjects would be retained for brands of cereals where the subjects may use different features that may be unique to one or more of the available set and therefore, MDS fit could be low since continuous dimensions rather than discrete features are assumed.

Another interesting implication of Table 3 is that there are subjects for whom the badness-of-fit criterion exceeds 0.25 which suggests that group stimulus space identified by weighted MDS (INDSCAL) may not represent some of the subjects accurately due to subject heterogeneity. In the interest of subject homogeneity, those subjects for whom the badness-of-fit exceeded 0.25 for three-dimensional solutions were dropped from further data analysis. Admittedly, this reduces the sample size for each of the three studies, impacting the study on brands of cereals the most and the study on fabrics the least, however increases subject homogeneity and allows for a clear interpretation of the findings when the stimuli configurations that are derived for perception and preference data are compared below.

5.3.4. Analysis of Similarity Data Using Weighted Multidimensional Scaling (MDS): Homogeneous Samples

The weighted MDS (INDSCAL) was repeated with the more homogeneous subset of the subjects of each type of stimuli as presented in Table 1 of Appendix 9. Actual sample sizes were 44, 32, and 24 for fabrics, transportation modes, and brands of cereals respectively.

The analysis was carried out for two, three, and four dimensions with an eye towards determining the number of dimensions to retain. How many dimensions to retain is one of the critical decisions in MDS and is somewhat similar in nature to the number of components / factors decisions in principal components and factor analyses. Keeping in mind that, everything else being constant parsimonious models are preferred over complex ones, the choice of the number of dimensions in unweighted MDS is guided by stress values, and interpretability and stability of obtained configurations for the stimuli (see an excellent discussion with examples in Kruskal and Wish 1978, p. 48-60). As for the use of stress values, a criterion that is often suggested is the elbow criterion, which is very similar to the interpretation of the "scree-plot" in factor analysis (Malhotra 1996; Whipple 1976; Mauser 1972; Shepard 1972). This criterion refers to the point at which an elbow occurs on the plot of the stress values against the number of dimensions. Beyond that number of dimensions that correspond to the elbow it is not desirable to add any dimensions. Since research over time has shown that the application of the "elbow" criterion was not very straightforward in many cases and the plot of stress values was very much affected by the error level in the data set, tables based on extensive simulations have been provided for UNWEIGHTED MDS against which the obtained stress values for an application can be compared (see Kruskal and Wish 1978, p. 48-60 and the references given therein). Unfortunately, there are no such published tables for WEIGHTED MDS (INDSCAL) and Kruskal and Wish (1978, p.63) note that "variance accounted for" is more customary that stress for INDSCAL. Shepard (1972) (also cited in Mauser 1972) argues that having more than three dimensions is justifiable in only very rare occasions since it usually adds little explanatory power to the model as compared with the complexity that it later involves in the interpretation phase of these dimensions. Shepard suggests a balance between parsimony, stability, and visualizability in addition to seeking improvement in goodness-of-fit.

Table 1 in Appendix 9 summarizes fit related weighted MDS results for two, three, and four dimensions when the homogeneous subset of the subjects are used. As expected, the mean badness-of-fit statistic improves due to eliminating some of the subject heterogeneity for each stimulus type and for each level of dimensions as indicated by the related rows in Table 1. If the rows for mean badness-of-fit statistic for the homogeneous versus whole sample are compared, it is noticed that limiting the analysis to the homogeneous sample improves the fit statistics, especially for transportation modes and brands of cereals for all dimensionalities that are considered.

The critical rows of Table 1 in Appendix 9 are the last two rows since they are related to the "variance accounted" suggested by Kruskal and Wish (1978, p. 63) and can be used in deciding the number of dimensions to keep as discussed above. Since squares of distances were fit to data and the data were assumed to be ordinal in nature, fit correlation in Table 1 represents the correlation between the squares of the monotonically transformed input data and the squares of the distances that are computed from the estimated coordinate matrix regarding each set of stimuli. Fit correlation squared that is presented in the last row is analogous to R^2 for a regression involving the squares of the monotonically transformed data as the dependent variable and the squares of the distances computed from the estimated coordinate matrix as the independent variable. Therefore, the entries in the last row reflect the variance accounted in the transformed squared distances by the squares of the distances derived from the estimated coordinate matrices.

An examination of these values suggests that even when only two dimensions are retained in the solutions, variance accounted for exceeds 0.80. Although these values are not highly impressive, they are still indicators of reasonably good fit given that multiple subjects were involved in each analysis. However, when the number of dimensions increases to three, there is a noticeable increase in variance accounted to 0.88 for fabrics, 0.90 for transportation modes and 0.85 for brands of cereals with increases of 0.05, 0.05, and 0.04, respectively. While the parsimony principle favors two-dimensional solutions, goodness-of-fit concerns suggest three dimensions. Note also that the improvement in variance accounted is relatively smaller with values less than or equal to 0.02 when the number of dimensions is increased from three to four for each type of stimuli.

Another critical criterion for deciding the number of dimensions is the interpretability of the derived stimulus space (Kruskal and Wish 1978; Shepard 1964). As discussed below, attempts to interpret the stimulus spaces for three-dimensional solutions for all three stimuli types were not successful and no meaningful interpretation could be given to the third dimension in each of the solutions. Furthermore, three-dimensional solutions are difficult to present geometrically and even with advanced graphical capabilities the proximity relationships among the stimuli can be difficult to describe. Given these concerns, it was decided to retain two dimensions for each of the stimuli sets. Interpretability of the final stimuli configuration is discussed further below when the configurations for both the perception and the preference data are examined through PROFIT, property fitting.

5.3.5. Analysis of Preference Data –Multidimensional Preference Analysis (MDPREF)

The next major data analysis step involved using the collected preference data to conduct a multidimensional preference analysis (MDPREF), an algorithm developed mainly by Carroll and Chang in the late sixties (Carroll 1972; see Green and Rao 1972, p. 212-214 and Green and Wind 1973, p. 327-328 for a discussion of the related computed program and computational details.) This type of analysis, also referred to as *unfolding*, allows the representation of the stimuli in a multidimensional space, based on the preferences of the respondents (Wish 1971). The related model is classified as an internal analysis of preferences.

Kuhfeld (2004, p. 746) notes that MDPREF is basically a principal component analysis of the (n x m) matrix of preference ratings of n products by m consumers. The data are stored as the transpose of the typical data matrix where the columns rather than the rows represent the subjects. After applying singular value decomposition to the data matrix, the standardized principal component scores are obtained for a predetermined number of underlying components (dimensions). A plot of the component scores as the coordinate values for the related stimuli gives the stimulus space based on the preferences. The first principal component represents the information that is most salient to the preference judgements. The second component represents the direction that is most salient to the preference judgements that is orthogonal to the first principal component (Kuhfeld 2004, p. 747), and so on for other dimensions.

A very important assumption in multidimensional unfolding is that all the individuals forming the sample of respondents perceive the stimuli in essentially the same way (Borg and Groenen 1997). This assumption reinforced our rationale to use homogeneous samples of participants, and therefore, we used exactly the same samples of subjects that we used for our weighted MDS analysis for the three stimuli sets under investigation. Using the same sample of respondents for the analysis of perception and preference data is meaningful because the major objective of the study is to compare the derived coordinate values for the preferences and perceptions. Each comparison is sound if the configurations derived from perception and preference data are based on the judgements of the same subjects.

MDPREF was run by using the PRINQUAL procedure in SAS. In each of the three studies, the subjects' ratings of nine stimuli in terms of their preferences were used as the input data. The results of the analyses in terms of the proportion of variance accounted by two, three and four dimensions are presented in Table 1 of Appendix 10. It is interesting to note that only two dimensions extract 97.10% of the total variance in the preference data for fabrics. This is not very surprising since the stimuli that were used were selected such that they varied along two dimensions. For transportation modes and brands of cereals, the proportion of variance accounted by two dimensions is 83.58% and 85.59%, respectively. While these levels are not highly impressive, still a substantial proportion of the total variance in the data is accounted by two dimensions only. When the number of dimensions is increased to three for these two types of stimuli, the variance accounted for increases to 93.94% and 95.41%, in each case representing about 10 percent increases. This can obviously be used as a reason to retain three dimensions. However, attempts to interpret the third dimensions were not very successful as in weighted MDS and for reasons of parsimony, ease of interpretation and presentation, two dimensions were retained for all stimuli. This also makes it easier to compare the derived stimulus spaces for perception and preference data because two dimensions are retained also for the stimulus spaces derived by unweighted MDS as discussed above.

As we saw, in an analysis of this nature *ideal points* reflecting individuals' preferences are typically added to the plot obtained but very importantly, and as we will see from the output resulting from MDPREF, we chose not to add those ideal points to the plots. The reason for this decision is based on the fact that we were not interested in individual subjects' preferences themselves, but more in the *underlying dimensions* used by the respondents. Adding additional information to the plots would only have complicated the interpretation phase of the analysis and shaded the information in which we were really interested.

5.3.6. Rotation of the Coordinates Obtained from MDPREF to Maximum Congruence with the Coordinates Obtained from Weighted MDS

The orientation of the axes for the stimulus spaces in MDS in general and also MDPREF are not unique. That is, the axes can be rigidly rotated by preserving the original angle between the axes. Also, the axes can be flipped since these transformations do not affect the distances between the stimuli. For this reason, it is not possible to directly compare the stimulus spaces obtained from MDS and MDPREF. Therefore, the coordinates of the MDPREF solution were orthogonally rotated to maximum congruence with the weighted MDS solution to be able to compare the two solutions and examine the degree of correspondence in the coordinate values.

For orthogonal rotation, Cliff's (1966) method was used. Such rotations preserve the distances between the coordinates of the stimuli (Borg and Groenen 1997; Dillon and Goldstein 1984; Davison 1983). Let A_1 be the $(n \times m)$ matrix of n stimuli in m dimensions obtained from weighted MDS, and B be the $(n \times m)$ matrix of n stimuli in m dimensions obtained from MDPREF. A_1 can be taken as the target and B can be orthogonally rotated to maximum congruence with A_1. For this purpose, a singular value decomposition of the matrix product $A_1^T B$ is needed:

$$A_1^T B = U \Lambda V^T$$

Where the matrix Λ is diagonal with ordered positive entries. The square matrix Λ^2 contains the eigenvalues of $A_1^T B B^T A_1$, and U and V are each orthonormal matrices. Let $T = VU^T$. Then, the loadings matrix B can be rotated to maximum congruence to A_1 to obtain $BT = A_2$. Thus A_1 and A_2 represent the coordinate matrices for the weighted MDS and MDPREF solutions where A_2 represents B after it has been rotated to maximum congruence to A_1.

Tables 2, 3 and 4 in Appendix 10 present the coordinate values on two dimensions for the weighted MDS and MDPREF solutions following the rotation of the MDPREF solution to maximum congruence to weighted MDS solution for fabrics, transportation modes and brands of cereals, respectively. An inspection of the coordinate values for corresponding dimensions of the weighted MDS and MDPREF solutions shows that the values are remarkably similar both in terms of their magnitude and sign. Before proceeding on to a test of the hypotheses of the study, a final criterion, that is the interpretability of the derived stimulus spaces, is checked to see if the resultant configurations for perceptions and preferences are meaningful for the two-dimensional solutions.

5.4. Interpretation of Stimulus Spaces in Weighted MDS and MDPREF solutions: PROFIT and PREFMAP

MDS configurations may be interpreted by researchers by systematically associating the positions in the configuration with some known characteristics of the stimuli that were scaled (Kruskal and Wish 1978). The researcher simply looks at the plot of the stimuli and attempts to recall what is known about them and to relate those known characteristics to the relative positions of the stimuli.

Kruskal and Wish (1978, p.30-44) suggest that the multidimensional stimulus configurations in MDS can be interpreted by taking a dimensional or a neighborhood approach. In the dimensional approach, one looks for "[...] lines in the space, possibly at right angles to each other, such that the stimuli projecting at opposite extremes of a line differ from each other in some easily describable way." (Kruskal and Wish 1978, p. 31). In the neighborhood interpretation of MDS configurations, "[...] neighborhoods or regions of the multidimensional space may have meaning associated with other shared characteristics" of the stimuli (Kruskal and Wish 1978, p. 44). The two approaches may reveal different kinds of insights regarding the relationships among the stimuli since in the neighborhood interpretation the focus primarily is on the small distances (similarities) while a dimensional approach focuses mainly on the large distances (dissimilarities).

Multiple linear regression can also be used for dimensional interpretation (Kruskal and Wish 1978, p. 35). If we have some additional measurements such as ratings on stimuli attributes and expect them to have a relationship with the relative positions of the stimuli in the configurations, each attribute rating may be regressed over the coordinate values of the configuration to interpret the configuration. Mathematically speaking, the attribute ratings are taken as the dependent variables in multivariate multiple regression and the coordinates of the stimuli, as estimated by weighted multidimensional scaling analysis (WMDS) are regarded as the independent variables. In the current case, since we have two-dimensional solutions, each attribute rating can be regressed on two independent variables:

$$Y = \beta_0 + X_1\beta_1 + X_2\beta_2 + \in$$

Where Y corresponds to the average ratings regarding an object attribute (e.g., thickness for fabrics, expensiveness for transportation modes, etc), X_1 , and X_2 are the stimulus coordinates for all objects on the two dimensions as estimated by WMDS, and $\in$ is the vector of error terms. The following formula can consequently be used:

$$\widetilde{Y} = \widetilde{X}\widetilde{\beta} + \widetilde{\in}$$

Where $\widetilde{Y}$ is a vector representing the *average* ratings of the respondents on each attribute separately, $\widetilde{X}$ is a matrix of coordinate values as estimated by weighted MDS or principal component scores as estimated in MDPREF for *n* stimuli objects and in *k* dimensions (in our case, $k = 2$), the $\widetilde{\beta}$ vector denotes for the regression weights, and finally, $\widetilde{\in}$ represents the error term. The estimated regression coefficients are subsequently used to evaluate how much each independent variable (that is, the estimated coordinates on a given dimension) accounts for the dependent variable (that is, attribute ratings). Since this approach was originally proposed by Chang and Carroll and programmed by them to FIT additional PROperties into MDS configurations, it has been known as PROFIT (please see the description of the algorithm and the related computer program in Green and Wind 1973 p. 359-362). Property fitting within for stimulus spaces estimated by MDPREF is known as PREFMAP (Green and Wind 1973, p. 329-334).[2]

[2] There are differences between PROFIT and PREFMAP both in terms of the model and the algorithm used but they are not further elaborated here. Please see Green and Wind (1973) and the references therein for further details.

In PROFIT, the multiple correlation coefficient associated with each multiple regression and directional cosines based on regression coefficients are used to interpret each configuration. The multiple correlation coefficient reflects the degree of association between a given attribute rating and a weighted combination of the coordinates on the dimensions where the weights are the regression coefficients. Kruskal and Wish (1978, p. 37-38) recommend multiple correlation coefficients of 0.90 but also indicate that values exceeding 0.70 will suffice in many instances. A high regression coefficient indicates that the angle between the dimension and the direction of the associated rating scale is small and the related line L almost coincides with the underlying dimension. Thus, the related attribute describes the underlying dimension well. Kruskal and Wish (1978) also note that the coefficients should be statistically significant. To describe the direction of a line, say L in the space defined by the coordinate values, direction cosines $c_1, c_2, \ldots, c_k$ are used where k is the number of dimensions (in the current case $k=2$). Each direction cosine c_k is simply a normalized regression weight (Kruskal and Wish 1978, p. 87):

$$c_k = B_k \Big/ \sqrt{B_1^2 + B_2^2 + \ldots}\,.$$

For any vector of coordinate values x_i, the point $Y_i = \beta_0 + X_{i1}\beta_1 + X_{i2}\beta_2$ gives the perpendicular projection of x_i on the line L with directional cosines as indicated above. These projections indicate the extent to which each stimulus i is judged to have the property Y.

For ease of interpretation, the length of each line representing a given attribute is drawn in SAS into the space defined by the coordinate values in proportion to the variance accounted by each related regression equation. Therefore, the longer arrows indicate attributes that explain more of the variation in the linear combination of coordinate values.

5.4.1. Interpretation of Stimulus Spaces for Fabrics

The results of PROFIT are summarized in Tables 1, 2, and 3 of Appendix 11 for fabrics, transportation modes and brands of cereals, respectively. Each table presents the overall F-value associated with each regression equation using each of the three attribute ratings as the dependent variable and the coordinate values of the stimuli as the independent variables. While the left half of each table presents the results for the weighted MDS solution, the right half summarizes the results for the MDPREF solution. Since the coordinate values derived by weighted MDS and rotated MDPREF solutions are very similar, not surprisingly very similar regression results are obtained. For this reason, only the left half of each table related to the regression results involving the relationship between each of the three attribute ratings and the coordinate values estimated by weighted MDS is discussed. This means that the interpretation of the underlying dimensions will be the same for perceptions and preferences for all three stimuli, an important result that we return to below as far as the three major hypotheses of the study are concerned.

According to Table 1 in Appendix 11, thickness, softness and perceived comfort level are all related to the first dimension of stimulus space for fabrics. R-square values for the related regression equations are 0.789 or above with associated p-values of 0.009 or less suggesting significant relationships between average ratings of each attribute and the coordinate values for the stimuli. Examining the signs of the regression coefficients 0.836, -0.789, and -0.671 for thickness, softness, and comfort respectively, thickness is positively and softness and comfort are negatively associated with dimension 1. These conclusions are reflected in Graph 1 of Appendix 12 where perceived fabric thickness increases in the direction of the related arrow along dimension 1, and softness and comfort increases in the other direction. Also, the fact that R-square associated with comfort is less than that for softness is reflected in a shorter arrow where all arrows originate from the origin (0,0). Therefore, dimension 1 reflects all three attributes "thickness", "softness" and "comfort". Given that the subjects were instructed to look for a fabric for a blouse for a graduation ball during summer, this dimension of overall comfort involving thickness and softness is not surprising. Also, it is related to finished weight of the fabric as given in Table 1 of Appendix 3 where fabric A is the heaviest fabric, C, D, E and F are moderate weight and B, H, and G are the lightest.

It is interesting to note that the perceptual map in Graph 1 of Appendix 12 has similarities to the map constructed by the researchers and expert fabric designer as presented in Table 1 of Appendix 3. If Graph 1 is rotated 90 degrees counter clock-wise, a map somewhat similar to Table 2 of Appendix 3 is obtained, except for fabric F which is perceived by the subjects to be similar to fabric E rather than I and D as expected by the researchers.

5.4.2. Interpretation of Stimulus Spaces for Transportation Modes

Table 2 in Appendix 11 presents the PROFIT results for transportation modes and the related geometric display is presented in Graph 2 of Appendix 12. As the findings in

Table 2 suggest, how much effort a transportation mode requires is highly related to dimension 1. As presented in Graph 2 of Appendix 12, this dimension separates bicycle and walk from the rest of transportation alternatives. Note that the regression weight associated with required effort for dimension 1 is 0.978 which suggests that this direction almost coincides with dimension 1 (with associated F and p-values of 448.26 and 0.001, respectively). Dimension 1 also reflects perceived expensiveness of the transportation alternatives in the opposite direction. While cycling and walking are relatively inexpensive, taking a taxi, bus, metro, train involves monetary expenses. Therefore, dimension 1 involves effort and monetary cost. How time consuming the transportation modes are seem to be related to dimension 2 (with F and p-values of 4.72 and 0.072). However, the relationship is not very strong as indicated by R-square value of 0.588 and also a relatively short arrow from the origin in Graph 2 of Appendix 12. If this arrow is extended and the stimuli points are projected onto the arrow, it can be seen that bicycle and walking are seen as time consuming as bus, metro and train whereas lift by a friend, driving a car, shared drive and taking a taxi are seen as less time consuming. Dimension 2 seems to separate also public transportation alternatives with other more individual means of transportation.

5.4.3. Interpretation of Stimulus Spaces for Brands of Cereals

Table 3 in Appendix 11 summarized the PROFIT results for brands of cereals and the related geometric display is presented in Graph 3 of Appendix 12. As presented in Table 3, all three attributes (filling, healthy, and provides lots of energy) are significantly related to the coordinate values with associated R-square values of 0.660, 0.869, and

0.691 and the p-values of 0.039, 0.002, and 0.029 respectively. The high regression coefficient 0.704 for "healthy" on dimension 1 suggests that in the direction of the related arrow given in Graph 3, perceived healthiness of the various brands of cereals increases. If the projections of the cereals onto the arrow are drawn, it becomes apparent that Müslix, Raisin Bran, and Special K are perceived to be healthy whereas Frosted Flakes and Froot Loops are at the opposite end of the healthiness direction. The extent to which a brand of cereal is perceived to be filling and provider of energy is negatively related to the second dimension. Although these relationships are statistically significant with p-values of 0.03 and 0.026, the related regression coefficients are not high (with values of -0.395 and -0.249) suggesting that the direction of "filling" and "provides lots of energy" does not highly coincide with the direction of the second dimension. By projecting the stimuli to the related arrows in Graph 3, we can see that Müslix, Raisin Bran, and Special K are perceived to be filling and providers of energy whereas Frosted Flakes and Froot Loops are at the opposite ends of these directions.

5.4.4. Summary: Interpretation of Retained Dimensions

The above discussion demonstrates that the two-dimensional stimulus spaces for fabrics, transportation modes, and various brands of cereals are rather meaningfully interpretable given prior information about the stimuli and also the attribute ratings that are projected into the stimulus spaces using regression. Although the meanings of the dimensions are interesting in themselves, the focus of the above analysis and the related discussion was to check if the retained dimensions could be easily interpreted. As mentioned before, interpretability is one of several critical considerations in determining the number of dimensions. While the two-dimensional solutions were interpretable, there was considerable difficulty in describing the additional dimension in three dimensions. Therefore, only two-dimensional solutions for perceptions and preferences were kept.

5.4.5. Calculation of the Correlations of Coordinate Values on Common Dimensions of Stimulus Spaces Resulting from WMDS and MDPREF Analyses

The discussion so far indicates that two-dimensional solutions for both perceptions and preferences and for each of the three stimuli types adequately capture sufficient amount of observed variance in the data, the derived stimulus spaces are remarkably similar for perceptions and preferences, and the meanings of these dimensions are the same in the perceptual stimulus spaces as in the preference space. This last section focuses on the coordinate values themselves and examines more *directly* how similar they are across common dimensions for stimulus spaces based on perceived similarity and preference judgements. For this purpose, correlations of the coordinate values for the common dimensions of stimulus spaces derived from weighted MDS and rotated MDPREF solutions are calculated (refer to Tables 2, 3, and 4 of Appendix 10). These correlations range between 0.995 and 1.000 for all three stimuli sets studies suggesting that the coordinate values on the same dimensions for weighted MDS and rotated MDPREF solutions are remarkably similar and change in the same direction.

This strong finding underlines that for the two-dimensional solutions, the stimulus spaces for perceptions and preferences are extremely similar for all three types of stimuli. Therefore, the empirical data support Hypotheses 1 and 2 concerning the stimuli which can be naturally described in terms of continuous dimensions (fabrics) and stimuli which are high in the choice hierarchy (transportation modes) but does not support Hypothesis 3 which states that the stimulus spaces for perceptions and preferences are likely to *differ* when the stimuli are low in the choice hierarchy and that they can be described only in terms of differential discrete features rather than common continuous dimensions. The third hypothesis would have been supported had the correlation values for common dimensions (values on the diagonal) for brands of cereals been much lower with values much closer to 0.00 rather than the current values of 0.994 and up. Under those circumstances, the meanings of the dimensions could have been different for the stimulus space derived by MDPREF.

6. CONCLUSIONS, LIMITATIONS AND FUTURE RESEARCH

This study examined whether the stimulus spaces derived from perceived similarity and preference data were structurally congruent in terms of the retained number of dimensions and the estimated values of the coordinate values. It was hypothesized that such congruence would be observed for stimuli that could be naturally described in terms of continuous attributes (fabrics), and stimuli that are high in the choice hierarchy and therefore the subjects have to compare them along high level dimensions that are likely to be rather continuous rather than discrete features (transportation modes). However, such congruence was not expected for stimuli that are low in the choice hierarchy since different discrete features that are unique to one or a few of the stimuli can be used to compare the alternative stimuli (brands of cereals). The findings confirm our expectations regarding the first two hypotheses but not the third one. Indeed, the stimulus spaces based on the perceptual and preference data were all similar in terms of number of dimensions, estimated coordinate values and the meaning of the dimensions. Although the goodness-of-fit statistics did not allow a clear cut decision on the number of dimensions to keep for transportation modes and brands of cereals, given a number of dimensionality, the coordinate values estimated by weighted MDS and the rotated coordinate values estimated by MDPREF were extremely similar on common dimensions. This conclusion held true both for two and three-dimensional solutions.

A possible reason for the rejection of the hypothesis that the underlying multidimensional structure will not be congruent for perceived similarity and preference data when the stimuli are low in the choice hierarchy is that the subjects of the experiment may have responded to the brands of cereals in terms of rather abstract dimensions that are related to their image built by advertising rather than the specific features of the products. Since product packages were not available during the data collection sessions, the subjects may have based their judgements on image in general instead of specific features.

In summary, the findings of this study suggest that the structure of the stimulus spaces as derived from perceived similarity and preference data may be similar in terms of number of dimensions and the estimated coordinate values (positions) of the related stimuli.

The findings suggest that perceptual and preference structures as derived by multidimensional scaling algorithms may be similar. An interesting potential implication of this finding is that marketing efforts to change perceptual structures may directly affect the related preference structures. Although this type of a link is to be expected, it should be noted however that the current research has not directly focused on the nature of the link between stimulus spaces based on perceptions and preferences.

A more important implication of the findings is for the recent developments in sophisticated probabilistic multidimensional scaling models that use a multiple inventories of measurements on ratings, pairwise similarities and preference (Carroll and Green 1997; Ramsay 1980; 1991; McKay, Easly and Zinnes 1995; DeSarbo and Wu 2001). These models, through the use of information on multiple inventories of items improve the stability of fitted models and reduce the uncertainty associated with model parameters by reducing their variances. These models implicitly assume that the data involving perceptions and preferences are related to the same underlying stimulus space. The findings of the current study support this assumption and encourage further methodological development in this direction.

6.1. Limitations of the Study and Further Research

Like many other empirical studies in the social sciences, this study has some limitations that need to be spelled out. The above conclusions are based on only three different stimuli sets with university students. Replications of the study with different stimuli sets and other consumer groups are needed to establish the generalizability of the results. Especially, a replication with a set of stimuli that could be considered low in the choice hierarchy is needed to test the original hypothesis that the stimulus spaces would not be congruent for perceived similarity and preference data.

An important aspect of the data collection sessions may have contributed to the observed congruence of the obtained stimulus spaces. Since each subject first filled out a section of the questionnaire on pairwise similarity of a set of stimuli and then rated them in terms of preference, having considered the similarity of the stimuli may have primed the subjects to consider the attributes or dimensions that they may have thought about in the preference section of the questionnaire. This may have contributed to the observed congruence of the derived stimulus spaces. Note that reversing the order of the perceived similarity and preference sections does not overcome this problem. Further research should consider a "split-half" approach with a much larger sample, divide the sample in two, and estimate the stimulus space for perceived similarity data with one half of the sample, estimate the stimulus space for preferences data with the other half of the sample, and then compare the resultant stimulus spaces.

Another important limitation of the study is that, because of the need to study a homogeneous group of subjects, the sample was reduced by eliminating subjects for whom the goodness-of-fit statistics were poor. This reduction was especially strong for brands of cereals suggesting substantial subject heterogeneity in terms of perceptions and or preferences. This heterogeneity may very well be due to having a stimuli set that is low in the choice hierarchy and the subjects' use of discrete features differentially. By eliminating the subjects for whom the goodness of statistics are poor, we may have ended up with a group of subjects who perceive the stimuli similarly and created the conditions that are favorable to the rejection of the third hypothesis. A potential way out of this dilemma is to use a model such as the one that has been recently suggested by DeSarbo and Wu (2001) and that recognizes the subject heterogeneity in terms of multiple segments, and then test whether the fit of the model is good across the segments. Indeed, this approach should be used with the data sets for all three types of stimuli to examine model fit across possible segments. The joint analysis of perceptions and preferences should make model parameters more stable and reduce their variances especially if the underlying stimulus spaces are congruent as assumed.

A further limitation regarding our data collection instrument is that the order of presentation of the pairs of stimuli remained the same for all 50 questionnaires within each of the three experiments. Hence the pairs that were presented at the beginning, middle and end of the survey were presented in that order for all subjects. It is however known that as the respondents progress through the rating task, they often experience boredom and fatigue, which potentially influence similarity judgements (Jain and Pinson 1976; Johnson et al. 1990; Bijmolt and Wedel 1995, all cited in Bijmolt et al. 1998). Knowing that the serial position of the stimuli may have this effect, if a replication of this study was to be conducted, special attention should be put on randomizing the presentation order of the pairs of stimuli in order to balance any cross-adaptation effects (Schiffman et al. 1981).

While conducting the data collection sessions, some of our respondents expressed their feelings regarding the process in which they were taking part. MDS related data collection is typically perceived to be long and somewhat monotonous since it involves the same ratings for a large number of stimuli. Therefore, some subjects find the task quite demanding and time consuming The resultant fatigue and boredom can easily affect the results increasing "noise" in the data especially with the stimuli at the end of the questionnaire, which in this case corresponded to preference data.

Furthermore, in the fabric experiment, some of our participants revealed that they were experiencing difficulty to distinguish some fabrics from one another. This point in itself is not a weakness since some of the fabrics were selected *because* of their similarity. Several of these subjects nonetheless expressed during the blind-test task the need to compare the fabrics simultaneously in the preference and attribute rating sections, where the stimuli were presented one at a time.

Finally, some authors report that preference data are not as sensitive to data collection format as proximity (or similarity) data (Whipple 1976). Consequently, it is recommended to collect similarity data using multiple measures to record people's perceptions. Because the task as we had designed it was already time and effort consuming, we opted for a single type of measure of our subjects' perceptions, pairwise comparisons. Even if this decision may have compromised the reliability of our results, we believe that it would not have been realistic to do otherwise.

An unfortunate incident that took place during the data collection sessions should be mentioned. Indeed, during or just a few days before data collection, there was a public transit (bus and metro) strike in downtown Montreal, the location for data collection. The subject's perceptions of those modes of transportation may have been affected because of the strike since a large percentage of the subjects (students) use public transportation.

Again, we do not believe that the limitations mentioned above could have in any way shade the interesting findings of this study, but a replication of this study with other stimuli and consumer groups is certainly needed in order to retest the hypotheses and also increase the generalizability of our findings.

APPENDICES

APPENDIX 1: QUESTIONNAIRES USED FOR THE THREE STUDIES

1.1. Fabrics Experiment Questionnaire

PERCEPTIONS OF AND PREFERENCES FOR VARIOUS FABRICS

PART A: INTRODUCTION

Thank you for your participation!

You are about to participate in a study conducted for the Master's of Science in Administration program (John Molson School of Business) involving consumers' preference and similarity judgements. Since perceptions and preferences are very personal and vary from one person to another, there are no right or wrong responses to the judgements that will be asked of you. Feel free to express how you feel and what you think.

Be assured that the data you will provide will be strictly confidential and anonymous. You will not be asked to specify your identity anywhere on this questionnaire.

This study concerns your perceptions of and preferences for various fabrics.

It is the end of the school year and your graduation party is going to take place in the reception room of a five-star hotel mid June. Everybody is expected to be dressed formally and you have decided to buy a brand new blouse for the occasion. A nice supper will first be served, and you will then enjoy the rest of the evening with your friends on the dance floor. You definitely want to wear something special and also comfortable for the occasion.

Assume that the fabrics that I will present to you are available for you to choose from. Please touch each fabric keeping the end-use in mind and get a feel for the fabrics.

Think about their similarities and differences. Feel free to ask to touch the fabrics again to evaluate which fabrics are similar and which ones are different

When you are finished please wait for further instructions.

PART B: PERCEPTIONS OF PAIRWISE SIMILARITY

Please rate how similar or dissimilar the following pairs of fabrics are by putting an "X" on the scale. The closer your rating is to the upper end of the scale, the more similar the fabrics are. ***Again, keep in mind the use context described in the given scenario.***

	Very Dissimilar		Very Similar
Left Fabric – Right Fabric	0	______________________________	100
	Very Dissimilar		Very Similar
Left Fabric – Right Fabric	0	______________________________	100
	Very Dissimilar		Very Similar
Left Fabric – Right Fabric	0	______________________________	100
	Very Dissimilar		Very Similar
Left Fabric – Right Fabric	0	______________________________	100
	Very Dissimilar		Very Similar
Left Fabric – Right Fabric	0	______________________________	100
	Very Dissimilar		Very Similar
Left Fabric – Right Fabric	0	______________________________	100
	Very Dissimilar		Very Similar
Left Fabric – Right Fabric	0	______________________________	100

Left Fabric – Right Fabric	Very Dissimilar 0	____________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	____________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	____________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	____________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	____________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	____________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	____________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	____________________	Very Similar 100

Left Fabric – Right Fabric	Very Dissimilar 0	________________________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	________________________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	________________________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	________________________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	________________________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	________________________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	________________________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	________________________________	Very Similar 100

	Very Dissimilar		Very Similar
Left Fabric – Right Fabric	0	________________________________	100
	Very Dissimilar		Very Similar
Left Fabric – Right Fabric	0	________________________________	100
	Very Dissimilar		Very Similar
Left Fabric – Right Fabric	0	________________________________	100
	Very Dissimilar		Very Similar
Left Fabric – Right Fabric	0	________________________________	100
	Very Dissimilar		Very Similar
Left Fabric – Right Fabric	0	________________________________	100
	Very Dissimilar		Very Similar
Left Fabric – Right Fabric	0	________________________________	100
	Very Dissimilar		Very Similar
Left Fabric – Right Fabric	0	________________________________	100
	Very Dissimilar		Very Similar
Left Fabric – Right Fabric	0	________________________________	100

Left Fabric – Right Fabric	Very Dissimilar 0	______________________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	______________________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	______________________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	______________________________	Very Similar 100
Left Fabric – Right Fabric	Very Dissimilar 0	______________________________	Very Similar 100

Please stop until further instructions. Move onto the next page only when you are told to do so.

PART C: PREFERENCES FOR VARIOUS FABRICS

Please rate each fabric below in terms of how much you like or dislike it in the context described in the given scenario, by putting an "X" on the scale. The closer your rating is to the upper end of the scale, the more you like the fabric. ***Again, keep in mind the use context described in the given scenario.***

	Dislike Very Much		Like Very Much
Fabric 1	0	________________________________	100
Fabric 2	0	________________________________	100
Fabric 3	0	________________________________	100
Fabric 4	0	________________________________	100
Fabric 5	0	________________________________	100
Fabric 6	0	________________________________	100
Fabric 7	0	________________________________	100
Fabric 8	0	________________________________	100
Fabric 9	0	________________________________	100

Please go over your preferences above and think about how much you like each fabric versus the others. Feel free to change any ratings to reflect your relative preferences. That is, if you like a fabric more than a few others, your rating of that fabric should be higher. If you like two fabrics almost the same, your ratings of those fabrics should be almost equal.

Please stop until further instructions. Move onto the next page only when you are told to do so.

PART D: YOUR PERCEPTIONS OF VARIOUS FABRICS ALONG CERTAIN ATTRIBUTES

In this section, you will rate each fabric along various attributes of interest. You will simply express whether you **believe** that a fabric has a particular attribute and how much. Again, there are no right or wrong answers. What matters is your perceptions.

Please rate each fabric below in terms of how **thick** it is, by putting an "X" on the scale. The closer your rating is to the upper end of the scale, the more you perceive the fabric to be thick.

	Very Thin		Very **Thick**
Fabric 1	1	________________________	10
Fabric 2	1	________________________	10
Fabric 3	1	________________________	10
Fabric 4	1	________________________	10
Fabric 5	1	________________________	10
Fabric 6	1	________________________	10
Fabric 7	1	________________________	10
Fabric 8	1	________________________	10
Fabric 9	1	________________________	10

Please go over your ratings above and think about how thick each fabric is in comparison to others. Feel free to change your ratings to reflect your relative perceptions. That is, if you perceive a fabric to be thicker than others, your rating of that fabric should be higher. If you perceive two fabrics to be almost equally thick, your ratings of those fabrics should be almost equal.

Please rate each fabric below in terms of how **soft** it is, by putting an "X" on the scale. The closer your rating is to the upper end of the scale, the more you perceive the fabric to be soft.

	Very Rough		Very Soft
Fabric 1	1	______________________________	10
Fabric 2	1	______________________________	10
Fabric 3	1	______________________________	10
Fabric 4	1	______________________________	10
Fabric 5	1	______________________________	10
Fabric 6	1	______________________________	10
Fabric 7	1	______________________________	10
Fabric 8	1	______________________________	10
Fabric 9	1	______________________________	10

Please go over your ratings above and think about how soft each fabric is in comparison to others. Feel free to change your ratings to reflect your relative perceptions. That is, if you perceive a fabric to be softer than others, your rating of that fabric should be higher. If you perceive two fabrics to be almost equally soft, your ratings of those fabrics should be almost equal.

Please rate each fabric below in terms of how comfortable it is, by putting an "X" on the scale. The closer your rating is to the upper end of the scale, the more you perceive the fabric to be comfortable.

	Very Uncomfortable		Very **Comfortable**
Fabric 1	1	______________________________	10
Fabric 2	1	______________________________	10
Fabric 3	1	______________________________	10
Fabric 4	1	______________________________	10
Fabric 5	1	______________________________	10
Fabric 6	1	______________________________	10
Fabric 7	1	______________________________	10
Fabric 8	1	______________________________	10
Fabric 9	1	______________________________	10

Please go over your ratings above and think about how comfortable each fabric is in comparison to others. Feel free to change your ratings to reflect your relative perceptions. That is, if you perceive a fabric to be more comfortable than others, your rating of that fabric should be higher. If you perceive two fabrics to provide almost equally comfortable, your ratings of those fabrics should be almost equal.

Thank you!

PERCEPTIONS OF AND PREFERENCES FOR VARIOUS TRANSPORTATION MODES

PART A: INTRODUCTION

Thank you for your participation!

You are about to participate in a study conducted for the Master's of Science in Administration program (John Molson School of Business) involving consumers' preference and similarity judgements. Since perceptions and preferences are very personal and vary from one person to another, there are no right or wrong responses to the judgements that will be asked of you. Feel free to express how you feel and what you think.

Be assured that the data you will provide will be strictly confidential and anonymous. You will not be asked to specify your identity anywhere on this questionnaire.

This study concerns your perceptions of and preferences for various transportation modes. The following transportation modes are included in the study.

Car	**Bus**
Taxi cab	**Bicycle**
Metro	**Walk**
Train	**Shared-driving** *(taking turns driving and sharing the expenses)*
Lift from someone *(e.g., parents)*	

Please take a couple of minutes to think about the similarities and differences of these transportation modes.

Having thought about the transportation modes, consider the following **scenario:**

> **Assume that you own a car and it is the beginning of September. You are planning for your transportation mode to your school for the remainder of the month. You live in an apartment/house that is located at about 5 kilometers from your school situated downtown in a metropolitan area.**

Keep in mind the context described above and go over the transportation modes given earlier to evaluate which ones are similar and which ones are different.

PART B: PERCEPTIONS OF PAIRWISE SIMILARITY

Please rate how similar or dissimilar the following pairs of transportation modes are by putting an "X" on the scale. The closer your rating is to the upper end of the scale, the more similar the transportation modes are. ***Again, keep in mind the use context described in the given scenario.***

	Very Dissimilar	Very Similar
Bicycle – Bus	0____	100
	Very Dissimilar	Very Similar
Metro – Lift from someone	0____	100
	Very Dissimilar	Very Similar
Train – Car	0____	100
	Very Dissimilar	Very Similar
Shared-driving – Walk	0____	100
	Very Dissimilar	Very Similar
Taxi cab – Bicycle	0____	100
	Very Dissimilar	Very Similar
Lift from someone – Bus	0____	100
	Very Dissimilar	Very Similar
Car – Metro	0____	100

Walk – Train	Very Dissimilar 0	______________________________	Very Similar 100
Taxi cab – Shared-driving	Very Dissimilar 0	______________________________	Very Similar 100
Bicycle – Lift from someone	Very Dissimilar 0	______________________________	Very Similar 100
Bus – Car	Very Dissimilar 0	______________________________	Very Similar 100
Metro – Walk	Very Dissimilar 0	______________________________	Very Similar 100
Train – Taxi cab	Very Dissimilar 0	______________________________	Very Similar 100
Shared-driving – Bicycle	Very Dissimilar 0	______________________________	Very Similar 100
Car – Lift from someone	Very Dissimilar 0	______________________________	Very Similar 100

Walk – Bus	Very Dissimilar 0 ______	Very Similar 100
Taxi cab – Metro	Very Dissimilar 0 ______	Very Similar 100
Shared-driving – Train	Very Dissimilar 0 ______	Very Similar 100
Bicycle – Car	Very Dissimilar 0 ______	Very Similar 100
Lift from someone – Walk	Very Dissimilar 0 ______	Very Similar 100
Bus – Taxi cab	Very Dissimilar 0 ______	Very Similar 100
Metro – Shared-driving	Very Dissimilar 0 ______	Very Similar 100
Train – Bicycle	Very Dissimilar 0 ______	Very Similar 100

	Very Dissimilar		Very Similar
Walk – Car	0	________________	100
	Very Dissimilar		Very Similar
Taxi cab – Lift from someone	0	________________	100
	Very Dissimilar		Very Similar
Shared-driving – Bus	0	________________	100
	Very Dissimilar		Very Similar
Train – Metro	0	________________	100
	Very Dissimilar		Very Similar
Bicycle – Walk	0	________________	100
	Very Dissimilar		Very Similar
Car – Taxi cab	0	________________	100
	Very Dissimilar		Very Similar
Lift from someone – Shared-driving	0	________________	100
	Very Dissimilar		Very Similar
Bus – Train	0	________________	100

	Very Dissimilar	Very Similar
Metro -- Bicycle	0____	100
	Very Dissimilar	Very Similar
Walk – Taxi Cab	0____	100
	Very Dissimilar	Very Similar
Car – Shared-driving	0____	100
	Very Dissimilar	Very Similar
Lift from someone – Train	0____	100
	Very Dissimilar	Very Similar
Bus – Metro	0____	100

Please stop until further instructions. Move onto the next page only when you are told to do so.

PART C: PREFERENCES FOR VARIOUS TRANSPORTATION MODES

Please rate each transportation mode below in terms of how much you like or dislike it in the context described in the given scenario, by putting an "X" on the scale. The closer your rating is to the upper end of the scale, the more you like the transportation mode. ***Again, keep in mind the use context described in the given scenario.***

	Dislike Very Much		Like Very Much
Car	0	______________________________	100
Train	0	______________________________	100
Metro	0	______________________________	100
Walk	0	______________________________	100
Bicycle	0	______________________________	100
Taxi cab	0	______________________________	100
Bus	0	______________________________	100
Shared-driving	0	______________________________	100
Lift from someone	0	______________________________	100

Please go over your preferences above and think about how much you like each transportation mode versus the others. Feel free to change any ratings to reflect your relative preferences. That is, if you like a transportation mode more than a few others, your rating of that transportation mode should be higher. If you like two transportation modes almost the same, your ratings of those transportation modes should be almost equal.

Please stop until further instructions. Move onto the next page only when you are told to do so.

PART D: YOUR PERCEPTIONS OF VARIOUS TRANSPORTATION MODES ALONG CERTAIN ATTRIBUTES

In this section, you will rate each transportation mode along various attributes of interest. You will simply express whether you **believe** that a transportation mode has a particular attribute and how much. Again, there are no right or wrong answers. What matters is your perceptions.

Please rate each transportation mode below in terms of how **time consuming** it is, by putting an "X" on the scale. The closer your rating is to the upper end of the scale, the more you perceive the transportation mode to be time consuming. ***Again, keep in mind the use context described in the given scenario.***

	Not Highly Time consuming		Highly Time consuming
Car	1	________________________	10
Train	1	________________________	10
Metro	1	________________________	10
Walk	1	________________________	10
Bicycle	1	________________________	10
Taxi cab	1	________________________	10
Bus	1	________________________	10
Shared-driving	1	________________________	10
Lift from someone	1	________________________	10

Please go over your ratings above and think about how time consuming each transportation mode is in comparison to others. Feel free to change your ratings to reflect your relative perceptions. That is, if you perceive a transportation mode to be more time consuming than others, your rating of that transportation mode should be higher. If you perceive two transportation modes to be almost equally time consuming, your ratings of those transportation modes should be almost equal.

Please rate each transportation mode below in terms of how **expensive** it is, by putting an "X" on the scale. The closer your rating is to the upper end of the scale, the more you perceive the transportation mode to be expensive. ***Again, keep in mind the use context described in the given scenario.***

	Not Expensive at All		Very Expensive
Car	1	______________________________	10
Train	1	______________________________	10
Metro	1	______________________________	10
Walk	1	______________________________	10
Bicycle	1	______________________________	10
Taxi cab	1	______________________________	10
Bus	1	______________________________	10
Shared-driving	1	______________________________	10
Lift from someone	1	______________________________	10

Please go over your ratings above and think about how expensive each transportation mode is in comparison to others. Feel free to change your ratings to reflect your relative perceptions. That is, if you perceive a transportation mode to be more expensive than others, your rating of that transportation mode should be higher. If you perceive two transportation modes to be almost equally expensive, your ratings of those transportation modes should be almost equal.

Please rate each transportation mode below in terms of how much **physical effort** it requires, by putting an "X" on the scale. The closer your rating is to the upper end of the scale, the more you perceive the transportation mode to require a lot of physical effort. ***Again, keep in mind the use context described in the given scenario.***

	Does Not Require Lots of Exercise		Requires Lots of Exercise
Car	1	______________________________	10
Train	1	______________________________	10
Metro	1	______________________________	10
Walk	1	______________________________	10
Bicycle	1	______________________________	10
Taxi cab	1	______________________________	10
Bus	1	______________________________	10
Shared-driving	1	______________________________	10
Lift from someone	1	______________________________	10

Please go over your ratings above and think about how much exercise each transportation mode requires in comparison to others. Feel free to change your ratings to reflect your relative perceptions. That is, if you perceive a transportation mode requires more exercise than others, your rating of that transportation mode should be higher. If you perceive two transportation modes to require almost equal exercise, your ratings of those transportation modes should be almost equal.

Thank you!

1.2. Brands of Cereals Experiment Questionnaire

PERCEPTIONS OF AND PREFERENCES FOR VARIOUS BRANDS OF CEREALS

PART A: INTRODUCTION

Thank you for your participation!

You are about to participate in a study conducted for the Master's of Science in Administration program (John Molson School of Business) involving consumers' preference and similarity judgements. Since perceptions and preferences are very personal and vary from one person to another, there are no right or wrong responses to the judgements that will be asked of you. Feel free to express how you feel and what you think.

Be assured that the data you will provide will be strictly confidential and anonymous. You will not be asked to specify your identity anywhere on this questionnaire.

This study concerns your perceptions of and preferences for various brands of cereals. The following brands are included in the study.

Cheerios	**Corn Flakes**
Rice Krispies	**Müslix**
Frosted Flakes	**Froot Loops**
Special K	**Mini-Wheats**
Raisin Bran	

Please take a couple of minutes to think about the similarities and differences of these brands. When you are finished please wait for further instructions.

Having thought about the cereal brands, consider the following **scenario:**

It is Saturday and early in the morning on a cold January day, and you are getting ready to head up North for a full weekend of sport activities (skiing, skating, or hiking) with your friends. Although you had a rough and busy week at school, you are looking forward to this demanding activity to get rid of some of your stress. You have a 2-hour drive and a big day ahead.

Keep in mind the context described above and go over the brands of cereals given earlier to evaluate which brands are similar and which ones are different.

PART B: PERCEPTIONS OF PAIRWISE SIMILARITY

Please rate how similar or dissimilar the following pairs of brands of cereals are by putting an "X" on the scale. The closer your rating is to the upper end of the scale, the more similar the brands are. ***Again, keep in mind the use context described in the given scenario.***

	Very Dissimilar		Very Similar
Corn Flakes – Frosted Flakes	0	____________________	100
Froot Loops – Rice Krispies	0	____________________	100
Cheerios – Raisin Bran	0	____________________	100
Müslix – Mini-Wheats	0	____________________	100
Special K – Corn Flakes	0	____________________	100
Rice Krispies – Frosted Flakes	0	____________________	100
Raisin Bran – Froot Loops	0	____________________	100

	Very Dissimilar		Very Similar
Mini-Wheats – Cheerios	0	____________________	100
	Very Dissimilar		Very Similar
Special K – Müslix	0	____________________	100
	Very Dissimilar		Very Similar
Corn Flakes – Rice Krispies	0	____________________	100
	Very Dissimilar		Very Similar
Frosted Flakes – Raisin Bran	0	____________________	100
	Very Dissimilar		Very Similar
Froot Loops – Mini-Wheats	0	____________________	100
	Very Dissimilar		Very Similar
Cheerios – Special K	0	____________________	100
	Very Dissimilar		Very Similar
Müslix – Corn Flakes	0	____________________	100
	Very Dissimilar		Very Similar
Raisin Bran – Rice Krispies	0	____________________	100

	Very Dissimilar		Very Similar
Mini-Wheats – Frosted Flakes	0	______________________________	100
	Very Dissimilar		Very Similar
Special K – Froot Loops	0	______________________________	100
	Very Dissimilar		Very Similar
Müslix – Cheerios	0	______________________________	100
	Very Dissimilar		Very Similar
Corn Flakes – Raisin Bran	0	______________________________	100
	Very Dissimilar		Very Similar
Rice Krispies – Mini-Wheats	0	______________________________	100
	Very Dissimilar		Very Similar
Frosted Flakes – Special K	0	______________________________	100
	Very Dissimilar		Very Similar
Froot Loops – Müslix	0	______________________________	100
	Very Dissimilar		Very Similar
Cheerios – Corn Flakes	0	______________________________	100

	Very Dissimilar		Very Similar
Mini-Wheats – Raisin Bran	0	____________________	100
	Very Dissimilar		Very Similar
Special K – Rice Krispies	0	____________________	100
	Very Dissimilar		Very Similar
Müslix – Frosted Flakes	0	____________________	100
	Very Dissimilar		Very Similar
Cheerios – Froot Loops	0	____________________	100
	Very Dissimilar		Very Similar
Corn Flakes – Mini-Wheats	0	____________________	100
	Very Dissimilar		Very Similar
Raisin Bran – Special K	0	____________________	100
	Very Dissimilar		Very Similar
Rice Krispies – Müslix	0	____________________	100
	Very Dissimilar		Very Similar
Frosted Flakes – Cheerios	0	____________________	100

	Very Dissimilar	Very Similar
Froot Loops – Corn Flakes	0________________________________	100
	Very Dissimilar	Very Similar
Mini-Wheats – Special K	0________________________________	100
	Very Dissimilar	Very Similar
Raisin Bran – Müslix	0________________________________	100
	Very Dissimilar	Very Similar
Rice Krispies – Cheerios	0________________________________	100
	Very Dissimilar	Very Similar
Frosted Flakes – Froot Loops	0________________________________	100

Please stop until further instructions. Move onto the next page only when you are told to do so.

PART C: PREFERENCES FOR VARIOUS BRANDS OF CEREALS

Please rate each brand of cereal below in terms of how much you like or dislike it in the context described in the given scenario, by putting an "X" on the scale. The closer your rating is to the upper end of the scale, the more you like the brand. ***Again, keep in mind the use context described in the given scenario.***

	Dislike Very Much		Like Very Much
Cheerios	0	______________________________	100
Corn Flakes	0	______________________________	100
Rice Krispies	0	______________________________	100
Frosted Flakes	0	______________________________	100
Müslix	0	______________________________	100
Special K	0	______________________________	100
Raisin Bran	0	______________________________	100
Froot Loops	0	______________________________	100
Mini-Wheats	0	______________________________	100

Please go over your preferences above and think about how much you like each brand versus the others. Feel free to change any ratings to reflect your relative preferences. That is, if you like a brand more than a few others, your rating of that brand should be higher. If you like two brands almost the same, your ratings of those brands should be almost equal.

Please stop until further instructions. Move onto the next page only when you are told to do so.

PART D: YOUR PERCEPTIONS OF VARIOUS BRANDS OF CEREALS ALONG CERTAIN ATTRIBUTES

In this section, you will rate each brand of cereal along various attributes of interest. You will simply express whether you **believe** that a brand has a particular attribute and how much. Again, there are no right or wrong answers. What matters is your perceptions.

Please rate each brand below in terms of how **filling** it is, by putting an "X" on the scale. "Filling" here means "you feel that your stomach is full until your next meal". The closer your rating is to the upper end of the scale, the more you perceive the brand to be filling.

	Not Highly Filling		Highly Filling
Cheerios	1	______________________________	10
Corn Flakes	1	______________________________	10
Rice Krispies	1	______________________________	10
Müslix	1	______________________________	10
Frosted Flakes	1	______________________________	10
Froot Loops	1	______________________________	10
Special K	1	______________________________	10
Mini-Wheats	1	______________________________	10
Raisin Bran	1	______________________________	10

Please go over your ratings above and think about how filling each brand is in comparison to others. Feel free to change your ratings to reflect your relative perceptions. That is, if you perceive a brand to be more filling than others, your rating of that brand should be higher. If you perceive two brands to be almost equally filling, your ratings of those brands should be almost equal.

Please rate each brand below in terms of how **healthy** it is, by putting an "X" on the scale. The closer your rating is to the upper end of the scale, the more you perceive the brand to be healthy.

	Not Healthy at All		Very Healthy
Cheerios	1	________	10
Corn Flakes	1	________	10
Rice Krispies	1	________	10
Müslix	1	________	10
Frosted Flakes	1	________	10
Froot Loops	1	________	10
Special K	1	________	10
Mini-Wheats	1	________	10
Raisin Bran	1	________	10

Please go over your ratings above and think about how healthy each brand is in comparison to others. Feel free to change your ratings to reflect your relative perceptions. That is, if you perceive a brand to be more healthy than others, your rating of that brand should be higher. If you perceive two brands to be almost equally healthy, your ratings of those brands should be almost equal.

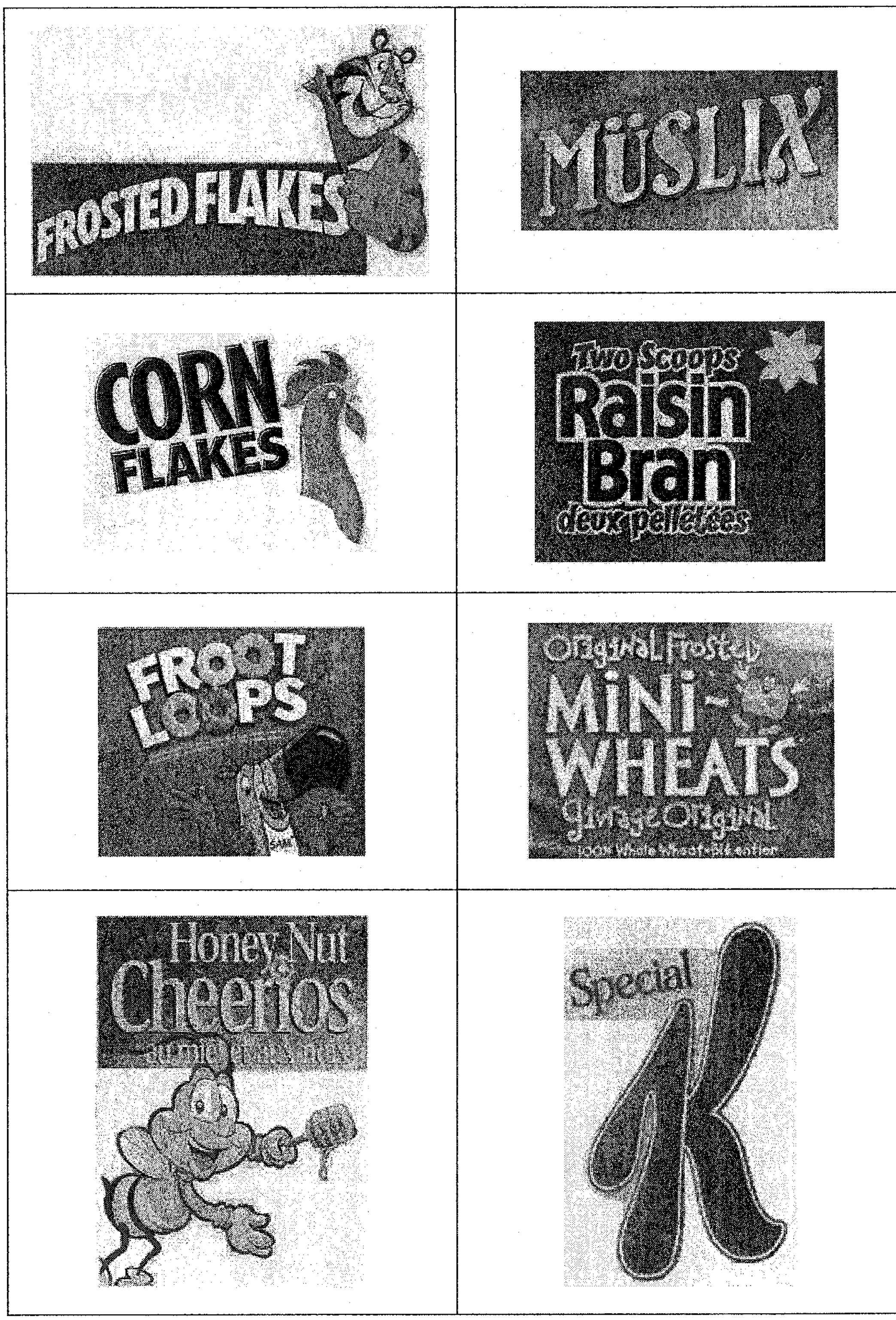
Please rate each brand below in terms of how much **energy** it provides, by putting an "X" on the scale. The closer your rating is to the upper end of the scale, the more you perceive the brand to provide lots of energy.

	Does Not Provide Lots of Energy		Provides Lots of Energy
Cheerios	1	______________________________	10
Corn Flakes	1	______________________________	10
Rice Krispies	1	______________________________	10
Müslix	1	______________________________	10
Frosted Flakes	1	______________________________	10
Froot Loops	1	______________________________	10
Special K	1	______________________________	10
Mini-Wheats	1	______________________________	10
Raisin Bran	1	______________________________	10

Please go over your ratings above and think about how much energy each brand provides in comparison to others. Feel free to change your ratings to reflect your relative perceptions. That is, if you perceive a brand provides more energy than others, your rating of that brand should be higher. If you perceive two brands to provide almost equal energy, your ratings of those brands should be almost equal.

Thank you!

APPENDIX 2: CEREAL LOGOS PRESENTED TO THE PARTICIPANTS FOR THE PURPOSE OF THE SECOND STUDY



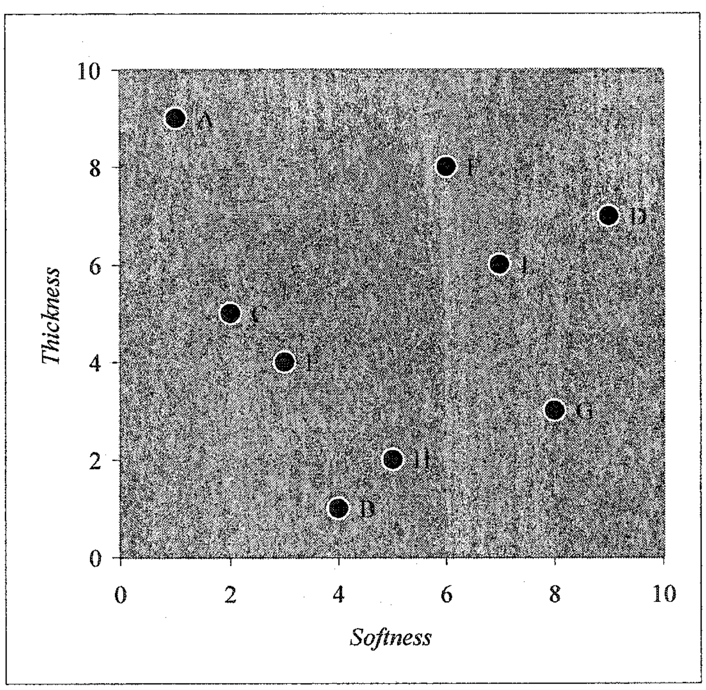
APPENDIX 3: CHARACTERISTICS OF THE SELECTED FABRICS

Table 1: Comparative Table of Selected Fabrics

Fabrics		
Label	**Reference #**	**Finished Weight (oz/yd^2)**
A	784827	10.0
B	401744	2.0
C	214300	5.1
D	281200	5.1
E	670400	6.5
F	294500	6.1
G	284800	2.7
H	260400	2.4
I	276600	7.5

Fibre content of all fabrics: 100% polyester composition.

Table 2: Approximate[3] Positioning of the Selected Fabrics on Two Dimensions



[3] The layout presented above is approximate and was determined by the two researchers with the guidance of the textile engineer expert that kindly helped the authors during the selection process of the fabric stimuli.

APPENDIX 4: EXAMPLE OF SYMMETRIC SIMILARITY MATRIX FOR TRANSPORTATION MODES

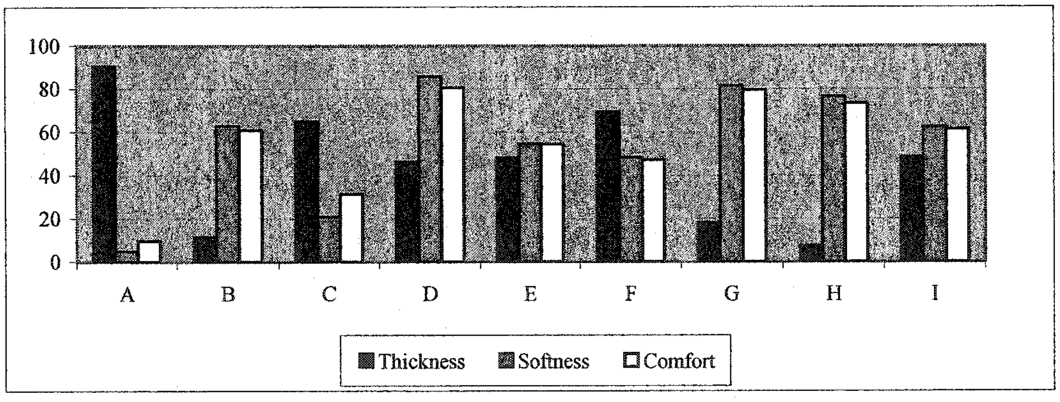
(For Subject No 1.)

	Car	Train	Metro	Walk	Bicycle	Taxi	Bus	Shareddr	Lift
Car	0	60.215	46.237	17.204	34.409	68.817	81.720	68.817	53.763
Train	60.215	0	61.290	19.355	29.032	43.011	69.892	34.409	51.613
Metro	46.237	61.290	0	19.355	25.806	34.409	86.021	49.462	82.796
Walk	17.204	19.355	19.355	0	59.140	22.581	16.129	21.505	17.204
Bicycle	34.409	29.032	25.806	59.140	0	47.312	32.258	33.333	43.011
Taxi	68.817	43.011	34.409	22.581	47.312	0	40.860	59.140	51.613
Bus	81.720	69.892	86.021	16.129	32.258	40.860	0	48.387	68.817
Shareddr	68.817	34.409	49.462	21.505	33.333	59.140	48.387	0	81.720
Lift	53.763	51.613	82.796	17.204	43.011	51.613	68.817	81.720	0

APPENDIX 5: MEAN VALUES FOR THREE ATTRIBUTE RATINGS FOR EACH STIMULUS TYPE

Table 1. Fabrics

Stimuli	*Attributes*		
	Thickness	Softness	Comfort
A	90.69	5.05	9.80
B	11.49	63.04	60.91
C	65.15	20.85	31.31
D	46.40	85.85	80.62
E	48.24	54.64	54.38
F	69.38	48.35	47.18
G	18.15	81.47	79.53
H	7.58	76.49	73.36
I	48.55	62.47	61.33



Correlation Coefficients Between the Attribute Ratings	
Correlation between:	
Thickness & Softness	-0.789
Softness & Comfort	0.995
Thickness & Comfort	-0.804

Thickness			**Softness**		
Stimuli	Predicted Coordinate Values[4]	Observed Coordinate Values	Stimuli	Predicted Coordinate Values	Observed Coordinate Values
A	90	90.69	*A*	10	5.05
B	10	11.49	*B*	40	63.04
C	50	65.15	*C*	20	20.85
D	70	46.40	*D*	90	85.85
E	40	48.24	*E*	30	54.64
F	80	69.38	*F*	60	48.35
G	30	18.15	*G*	80	81.47
H	20	7.58	*H*	50	76.49
I	60	48.55	*I*	70	62.47

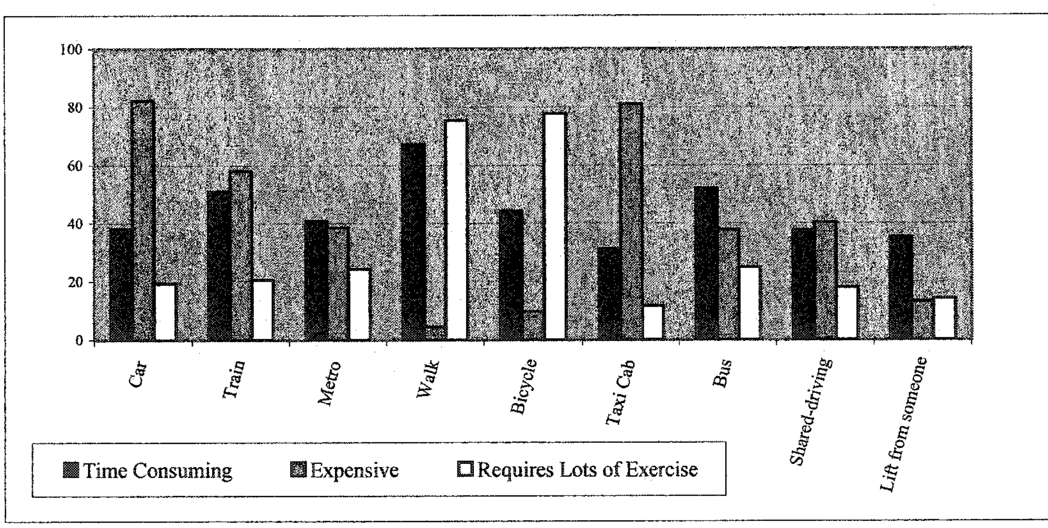
Correlation Coefficients Between Predicted Values and Observed Ratings[5]	
Correlation for:	
Thickness	0.905
Softness	0.848

[4] The "predicted coordinate values" displayed in this table refer to the approximate positioning of the selected fabrics as selected by the researchers and the textile expert and are also presented in table 2 of Appendix 3.

[5] Note that the correlation coefficients presented here were calculated for the fabrics stimuli only since this is the only stimuli set for which and expert could provide us objective insights on their positioning along two specific dimensions. Also, because as we will see further only two dimensions were retained, the comfort dimension and therefore the associated coordinate values were disregarded here.

Table 2. Transportation Modes

Stimuli	Time Consuming	Expensive	Requires Lots of Exercise
	Attributes		
Car	38.29	82.27	19.36
Train	51.00	58.07	20.69
Metro	40.89	38.65	24.47
Walk	67.24	4.56	75.51
Bicycle	44.36	9.82	77.78
Taxi Cab	31.36	81.04	11.76
Bus	52.20	37.87	25.02
Shared-driving	37.73	40.33	18.09
Lift from someone	35.38	13.24	14.22

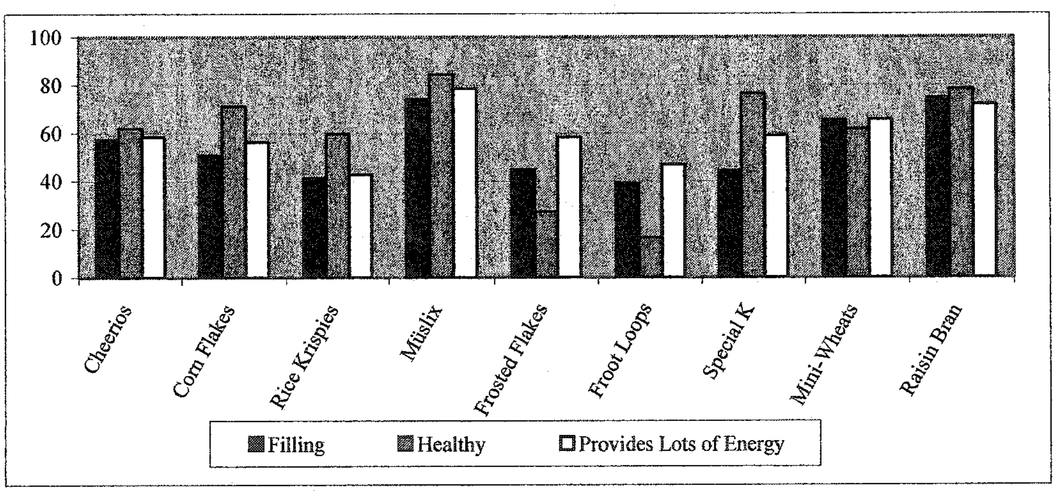


Correlation Coefficients Between the Attribute Ratings

Correlation between:	
Time Consuming & Expensive	-0.464
Expensive & Requires Lots of Exercise	-0.671
Time Consuming & Requires Lots of Exercise	0.640

Table 3. Brands of Cereals

Stimuli	*Attributes* Filling	Healthy	Provides Lots of Energy
Cheerios	57.51	62.16	58.49
Corn Flakes	50.91	71.31	56.36
Rice Krispies	41.42	59.84	42.82
Müslix	74.22	84.40	78.58
Frosted Flakes	44.89	27.36	58.33
Froot Loops	39.25	16.45	46.95
Special K	44.45	76.42	59.05
Mini-Wheats	65.49	61.71	65.69
Raisin Bran	74.80	78.27	71.98



Correlation Coefficients Between the Attribute Ratings	
Correlation between:	
Filling & Healthy	0.642
Healthy & Provides Lots of Energy	0.600
Filling & Provides Lots of Energy	0.908

APPENDIX 6: SUMMARY OF WEIGHTED MULTIDIMENSIONAL SCALING (MDS) AND MULTIDIMENSIONAL PREFERENCE (MDPREF) ANALYSES STEPS

Pairwise similarity judgements	Ratings along three selected attributes for each stimulus set	Pairwise preference judgements
Input to multidimensional scaling (SAS MDS)		Input to MDPREF (multidimensional preference analysis) (SAS PRINQUAL)
Determine the number of dimensions and the coordinates of the stimuli		Determine the number of dimensions and the coordinates of the stimuli
		Rotate coordinates to max. congruence with perceptual coordinates
Given the coordinates, do PROFIT (property fitting) (SAS TRANSREG)		Given the coordinates, do PREFMAP (preference mapping) (SAS TRANSREG)
For each rating, calculate R-Square (nb of R-Sq. = nb of selected attributes) ➔ Save the regression coefficients (βs[6])	**Compare coordinates and calculate the correlation of the coordinates.** • If strong correlation: the same dimensions are used for similarity and preference judgements. • If weak correlation: different dimensions are used for similarity and preference judgements.	For each rating, calculate R-Squares (nb of R-Sq. = nb of selected attributes) ➔ Save the regression coefficients (βs)

[6] If we assume a three-dimensional MDS solution: $Y_k = \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3$. The βêtas determine the direction of the dimensions.

APPENDIX 7: UNWEIGHTED MDS RESULTS OF INTEREST

Table 1: Badness-of-Fit Statistic for Individual Analysis of Similarity Data (Unweighted MDS)

Stimulus Type		*Number of Dimensions* 2	3	4
Fabrics	*Minimum*	0.04	0.02	0.01
	Maximum	0.25	0.10	0.07
	Mean	0.12	0.06	0.03
	Variance (s^2)	0.00175	0.00040	0.00019
	Std Dev. (s)	0.04186	0.01995	0.01373
Transportation Modes	*Minimum*	0.01	0.02	0.01
	Maximum	0.26	0.18	0.11
	Mean	0.13	0.06	0.03
	Variance (s^2)	0.00356	0.00116	0.00028
	Std Dev. (s)	0.05966	0.03402	0.01668
Brands of Cereals	*Minimum*	0.02	0.02	0.01
	Maximum	0.29	0.14	0.06
	Mean	0.14	0.07	0.03
	Variance (s^2)	0.00384	0.00083	0.00019
	Std Dev. (s)	0.06199	0.02875	0.01385

* The variance of a sample is a measure of the spread of the data about the mean.
Variance formula used:

$$\text{Sample Variance} = s^2 = \frac{\sum (x-\bar{x})^2}{n-1}$$

Where:

x : badness-of-fit criterion for each subject of the sample studied
$\bar{x}$: badness-of-fit criterion mean
n : sample size

* The standard deviation of a sample is the positive square root of the variance, but its property is that it is the same as the unit of measure of the data, in our case percentages (%).

Standard deviation formula used:

$$\text{sample standard deviation} = s = \sqrt{s^2}$$

Table 2: Comparative Table of the Number of Subjects That Would be Kept in Further Analysis Given Various Cut-Off Values for Badness-of-Fit Criterion (Unweighted MDS)

Stimulus Type	*Number of dimensions*	*Badness-of-Fit Criterion*		
		≤ 0.20	≤ 0.22	≤ 0.25
Fabrics	*2*	48	49	50
	3	50	50	50
	4	50	50	50
Transportation Modes	*2*	45	48	49
	3	50	50	50
	4	50	50	50
Brands of Cereals	*2*	43	45	48
	3	50	50	50
	4	50	50	50

APPENDIX 8: WEIGHTED MDS RESULTS OF INTEREST

Table 1: Badness-of-Fit Statistic for Similarity Data (Weighted MDS at the Group Level)

Stimulus Type		*Number of Dimensions* 2	3	4
Fabrics	*Minimum*	0.17	0.10	0.08
	Maximum	0.45	0.35	0.28
	Mean	0.27	0.20	0.16
	Variance (s^2)	0.00350	0.00224	0.00158
	Std Dev. (s)	0.05913	0.04738	0.03969
Transportation Modes	*Minimum*	0.12	0.09	0.08
	Maximum	0.50	0.39	0.30
	Mean	0.32	0.24	0.20
	Variance (s^2)	0.01133	0.00589	0.00297
	Std Dev. (s)	0.10644	0.07676	0.05445
Brands of Cereals	*Minimum*	0.20	0.14	0.11
	Maximum	0.49	0.38	0.31
	Mean	0.35	0.26	0.20
	Variance (s^2)	0.00563	0.00307	0.00249
	Std Dev. (s)	0.07502	0.05540	0.04986

Table 2: Comparative Table of the Number of Subjects That Would be Kept Given Various Cut-Off Values for Badness-of-Fit Criterion (Weighted MDS at the Group Level)

Stimulus Type	*Number of dimensions*	*Badness-of-Fit Criterion* ≤ 0.20	≤ 0.22	≤ 0.25
Fabrics	*2*	10	16	27
	3	29	37	44
	4	44	49	49
Transportation Modes	*2*	9	11	19
	3	22	27	32
	4	31	38	44
Brands of Cereals	*2*	1	2	6
	3	14	16	24
	4	27	39	45

APPENDIX 9: WEIGHTED MDS RESULTS OF INTEREST FOR HOMOGENEOUS GROUP OF RESPONDENTS

Table 1. Weighted MDS Results for Homogeneous Group of Respondents in Two, Three, and Four-Dimensional Solutions

	Stimulus Type								
	Fabrics			Transportation Modes			Brands of Cereals		
Number of Dimensions	**2**	**3**	**4**	**2**	**3**	**4**	**2**	**3**	**4**
Sample Size	44	44	44	32	32	32	24	24	24
Mean Badness-of-Fit Statistic (Homogeneous sample)	0.25	0.19	0.15	0.25	0.18	0.15	0.27	0.20	0.16
Mean Badness-of-Fit Statistic (Whole Sample)[7]	0.27	0.20	0.16	0.32	0.24	0.20	0.35	0.26	0.20
Distance Correlation[8]	0.88	0.90	0.94	0.90	0.93	0.94	0.89	0.91	0.93
Fit Correlation[9]	0.91	0.94	0.95	0.92	0.95	0.96	0.90	0.92	0.93
Fit Correlation Squared[10]	0.83	0.88	0.90	0.85	0.90	0.92	0.81	0.85	0.86

[7] The statistics in this row are copied from Table 1 of Appendix 8.
[8] Distance Correlation is the correlation between the monotonically transformed input data and the distances that are computed from the estimated coordinate matrix regarding each set of stimuli. A monotonic transformation is applied to the input data since the measurement level is assumed to be ordinal.
[9] Fit Correlation is the correlation between *squares* of the monotonically transformed data and the *squares* of the distances that are computed from the estimated coordinate matrix regarding each set of stimuli.
[10] Fit Correlation Squared is analogous to R^2 for a regression involving the squares of the monotonically transformed data as the dependent variable and the squares of the distances computed from the estimated coordinate matrix as the independent variable.

APPENDIX 10: MDPREF RESULTS OF INTEREST FOR HOMOGENEOUS GROUP OF RESPONDENTS

Table 1. Multidimensional Preference Analysis (MDPREF) Results for Homogeneous Groups of Respondents in Two, Three and Four-Dimensional Solutions

	Stimulus Type								
	Fabrics			Transportation Modes			Brands of Cereals		
Number of Dimensions	**2**	**3**	**4**	**2**	**3**	**4**	**2**	**3**	**4**
Number of Iterations before Convergence	168	569	373	133	613	712	90	562	2289
Proportion of Variance Accounted For (%)	97.10	98.26	100	83.58	93.94	99.25	85.59	95.41	99.21

Table 2: Stimulus Space for Weighted MDS and Rotated MDPREF Solutions for Fabrics

Coordinate Values for WMDS			Coordinate Values for Rotated MDPREF[11]		
Stimuli	Dimension 1	Dimension 2	Stimuli	Dimension 1	Dimension 2
A	1.777	1.155	*A*	1.609	0.975
B	-1.076	0.149	*B*	-1.032	0.215
C	1.287	0.450	*C*	1.192	0.339
D	-0.256	1.596	*D*	-0.353	1.534
E	0.418	-1.197	*E*	0.479	-1.166
F	0.516	-1.246	*F*	0.576	-1.219
G	-0.998	0.520	*G*	-0.984	0.563
H	-1.096	-0.156	*H*	-1.031	-0.072
I	-0.572	-1.271	*I*	-0.456	-1.169

Correlation coefficients between coordinate values derived from weighted MDS and rotated MDPREF:	0.997

[11] After rotation to maximum congruence with WMDS solution.

Table 3: Stimulus Space for Weighted MDS and Rotated MDPREF Solutions for Transportation Modes

Coordinate Values for WMDS			Coordinate Values for Rotated MDPREF		
Stimuli	Dimension 1	Dimension 2	Stimuli	Dimension 1	Dimension 2
Car	-0.529	-1.148	*Car*	-0.473	-1.071
Train	-0.609	1.323	*Train*	-0.605	1.262
Metro	-0.515	1.326	*Metro*	-0.516	1.263
Walk	1.900	0.148	*Walk*	1.790	0.096
Bicycle	1.800	0.179	*Bicycle*	1.695	0.129
Taxi Cab	-0.824	-0.650	*Taxi Cab*	-0.763	-0.594
Bus	-0.547	1.076	*Bus*	-0.540	1.028
Shared-driving	-0.448	-1.123	*Shared-driving*	-0.398	-1.050
Lift from someone	-0.228	-1.131	*Lift from someone*	-0.189	-1.062

Correlation coefficients between coordinate values derived from weighted MDS and rotated MDPREF:	1.000

Table 4: Stimulus Space for Weighted MDS and Rotated MDPREF Solutions for Brands of Cereals

Coordinate Values for WMDS			Coordinate Values for Rotated MDPREF		
Stimuli	Dimension 1	Dimension 2	Stimuli	Dimension 1	Dimension 2
Cheerios	0.276	1.542	*Cheerios*	0.419	1.506
Corn Flakes	0.029	0.022	*Corn Flakes*	0.030	0.024
Rice Krispies	0.903	1.026	*Rice Krispies*	0.969	1.074
Müslix	0.988	-0.958	*Müslix*	0.851	-0.819
Frosted Flakes	-1.441	0.085	*Frosted Flakes*	-1.373	-0.063
Froot Loops	-1.868	0.934	*Froot Loops*	-1.697	0.708
Special K	0.851	0.086	*Special K*	0.824	0.168
Mini-Wheats	-0.504	-1.276	*Mini-Wheats*	-0.611	-1.274
Raisin Bran	0.766	-1.461	*Raisin Bran*	0.587	-1.323

Correlation coefficients between coordinate values derived from weighted MDS and rotated MDPREF:	0.995

APPENDIX 11: REGRESSION RESULTS FOR ROTATED STIMULUS SPACES

Table 1: Regression Results for Rotated Stimulus Space Obtained from Weighted MDS and Rotated MDPREF for Fabrics

WEIGHTED MDS	*Attributes*		
	Thickness	Softness	Comfort
Overall F-Value	17.68	11.26	11.25
P-Value	0.003	0.009	0.009
R-Square	0.855	0.789	0.789
COEFFICIENTS:			
Dimension 1	0.836	-0.769	-0.671
F-Value	35.27	22.36	22.42
P-Value	0.001	0.003	0.003
Dimension 2	-0.081	0.047	0.059
F-Value	0.33	0.08	0.17
P-Value	0.586	0.78	0.69

ROTATED MDPREF	*Attributes*		
	Thickness	Softness	Comfort
Overall F-Value	17.62	11.26	11.25
P-Value	0.003	0.009	0.009
R-Square	0.855	0.789	0.789
COEFFICIENTS:			
Dimension 1	0.879	-0.810	-0.705
F-Value	35.33	22.51	22.49
P-Value	0.001	0.003	0.003
Dimension 2	-0.021	-0.009	0.011
F-Value	0.02	0.00	0.01
P-Value	0.88	0.960	0.943

Table 2: Regression Results for Rotated Stimulus Space Obtained from Weighted MDS and Rotated MDPREF for Transportation Modes

WEIGHTED MDS	*Attributes*		
	Time Consuming	Expensive	Requires Lots of Effort
Overall F-Value	4.29	3.51	240.31
P-Value	0.069	0.098	<0.001
R-Square	0.588	0.539	0.988
COEFFICIENTS:			
Dimension 1	0.184	-0.678	0.978
F-Value	3.45	6.66	448.26
P-Value	0.113	0.041	<0.001
Dimension 2	0.215	-0.123	0.216
F-Value	4.72	0.22	21.79
P-Value	0.072	0.655	0.003

ROTATED MDPREF	*Attributes*		
	Time Consuming	Expensive	Requires Lots of Effort
Overall F-Value	4.28	3.51	240.32
P-Value	0.068	0.098	<0.001
R-Square	0.588	0.539	0.988
COEFFICIENTS:			
Dimension 1	0.200	-0.722	1.042
F-Value	3.65	6.73	453.79
P-Value	0.105	0.041	<0.001
Dimension 2	0.232	-0.148	0.253
F-Value	4.92	0.28	26.83
P-Value	0.069	0.614	0.002

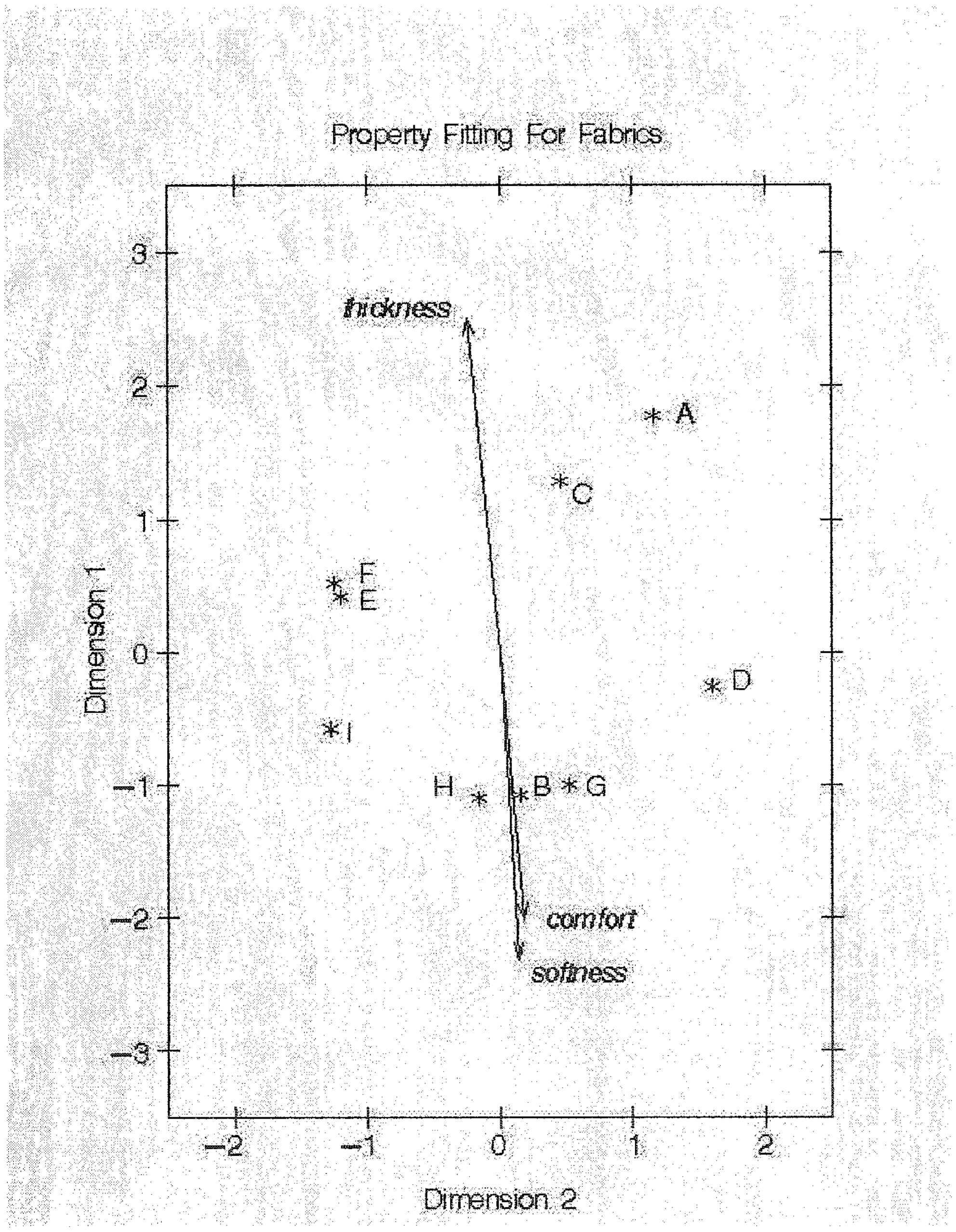
Table 3: Regression Results for Rotated Stimulus Space Obtained from Weighted MDS and Rotated MDPREF for Brands of Cereals

WEIGHTED MDS	*Attributes* Filling	Healthy	Provides Lots of Energy
Overall F-Value	5.83	19.96	6.73
P-Value	0.039	0.002	0.029
R-Square	0.660	0.869	0.691
COEFFICIENTS:			
Dimension 1	0.178	0.704	0.130
F-Value	1.63	30.95	2.36
P-Value	0.248	0.001	0.176
Dimension 2	-0.395	-0.225	-0.249
F-Value	8.03	3.16	8.66
P-Value	0.030	0.126	0.026

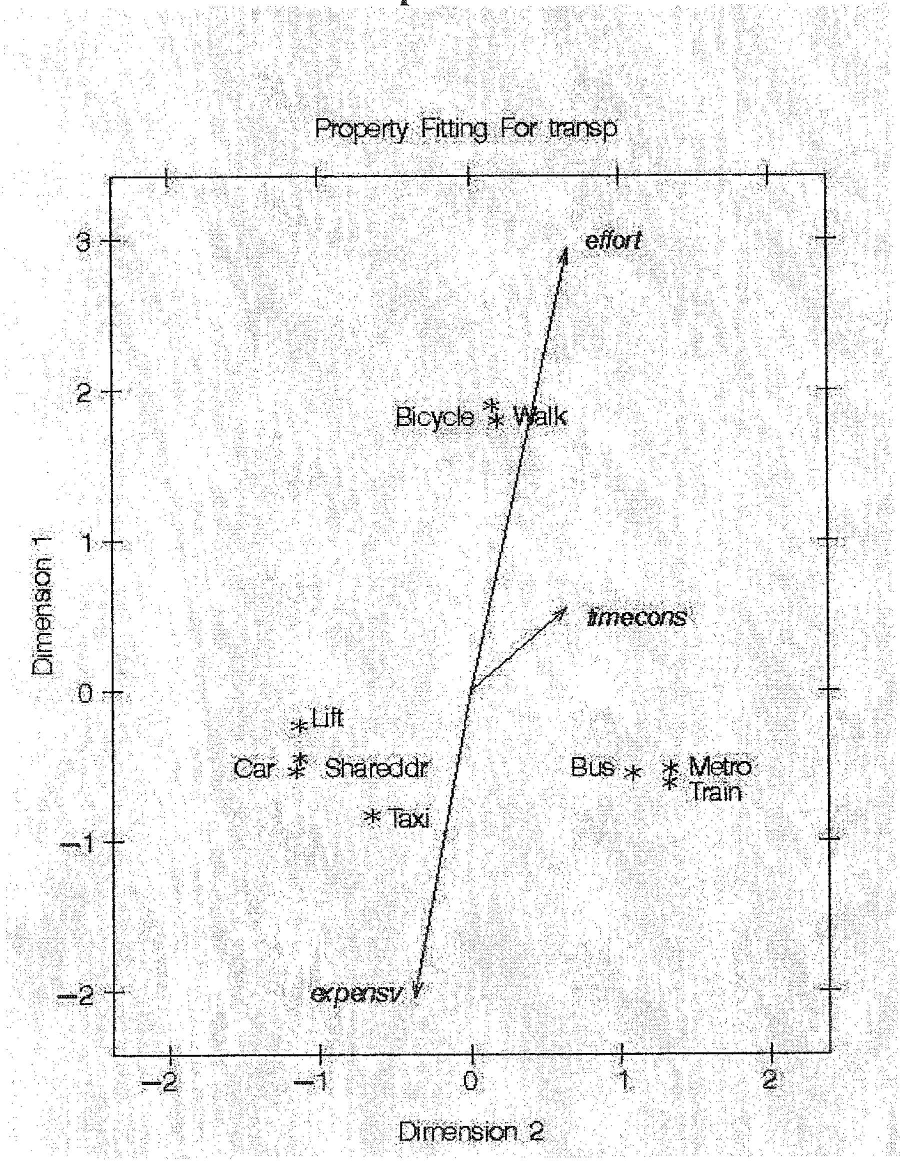
ROTATED MDPREF	*Attributes* Filling	Healthy	Provides Lots of Energy
Overall F-Value	5.83	19.96	6.73
P-Value	0.039	0.022	0.029
R-Square	0.660	0.869	0.691
COEFFICIENTS:			
Dimension 1	0.232	0.768	0.165
F-Value	2.56	34.17	3.51
P-Value	0.160	0.001	0.110
Dimension 2	-0.436	-0.315	-0.276
F-Value	9.10	5.76	9.95
P-Value	0.024	0.053	0.019

APPENDIX 12: STIMULUS SPACES OBTAINED FROM PERCEPTION JUDGEMENTS

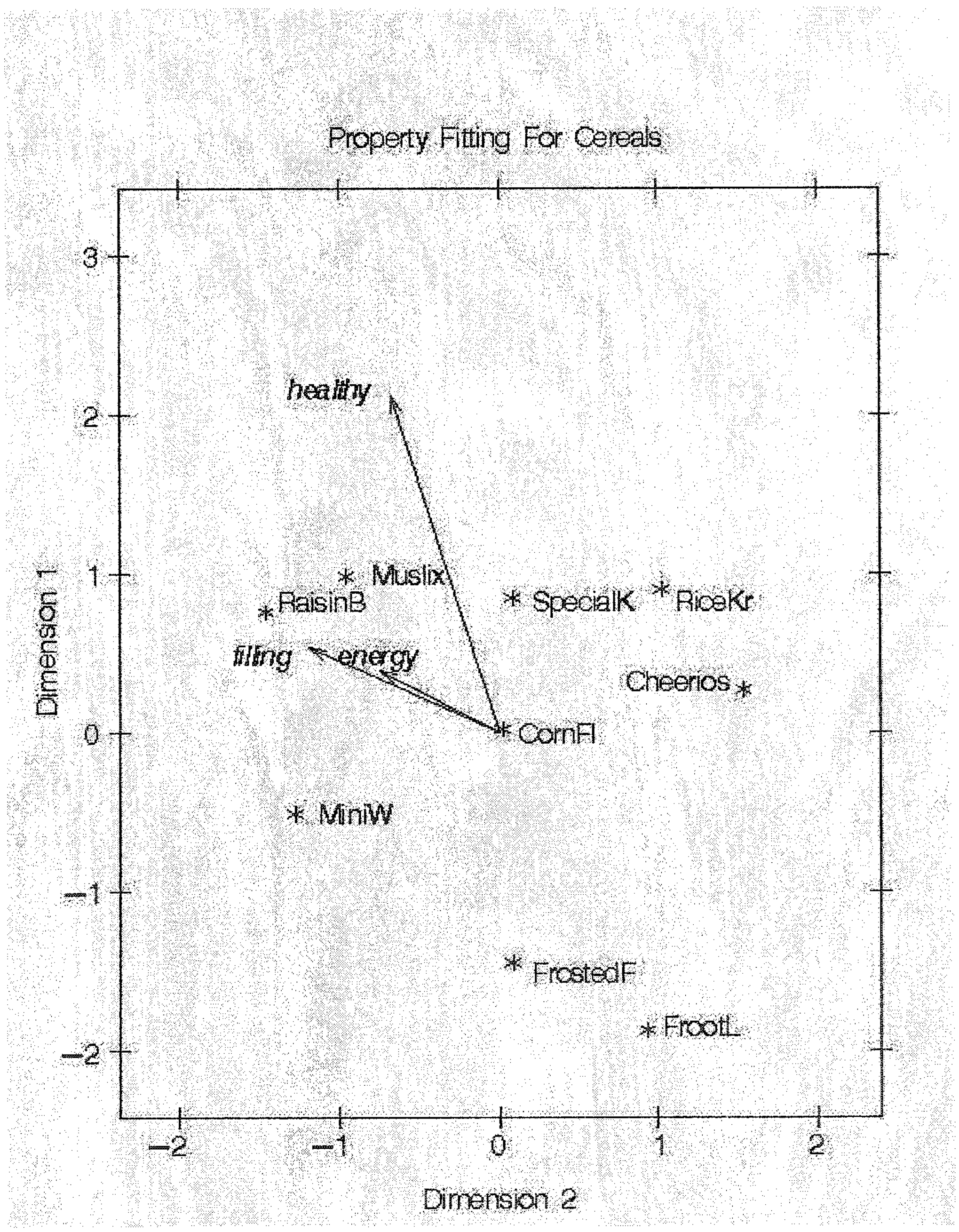
Graph 1: Two-Dimensional Perceptual Map and Property Fitting for Fabrics



Graph 2: Two-Dimensional Perceptual Map and Property Fitting for Transportation Modes

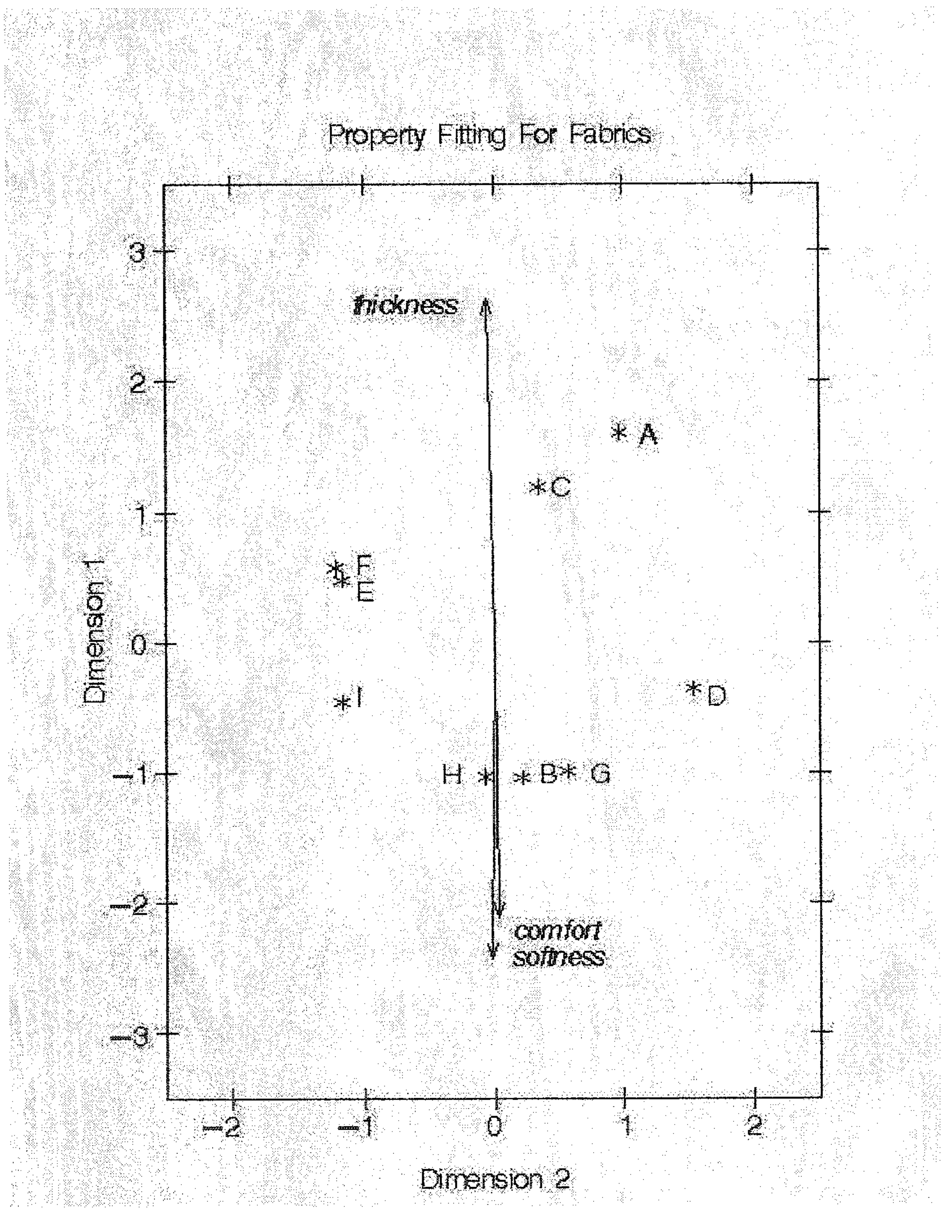


Graph 3: Two-Dimensional Perceptual Map and Property Fitting for Brands of Cereals

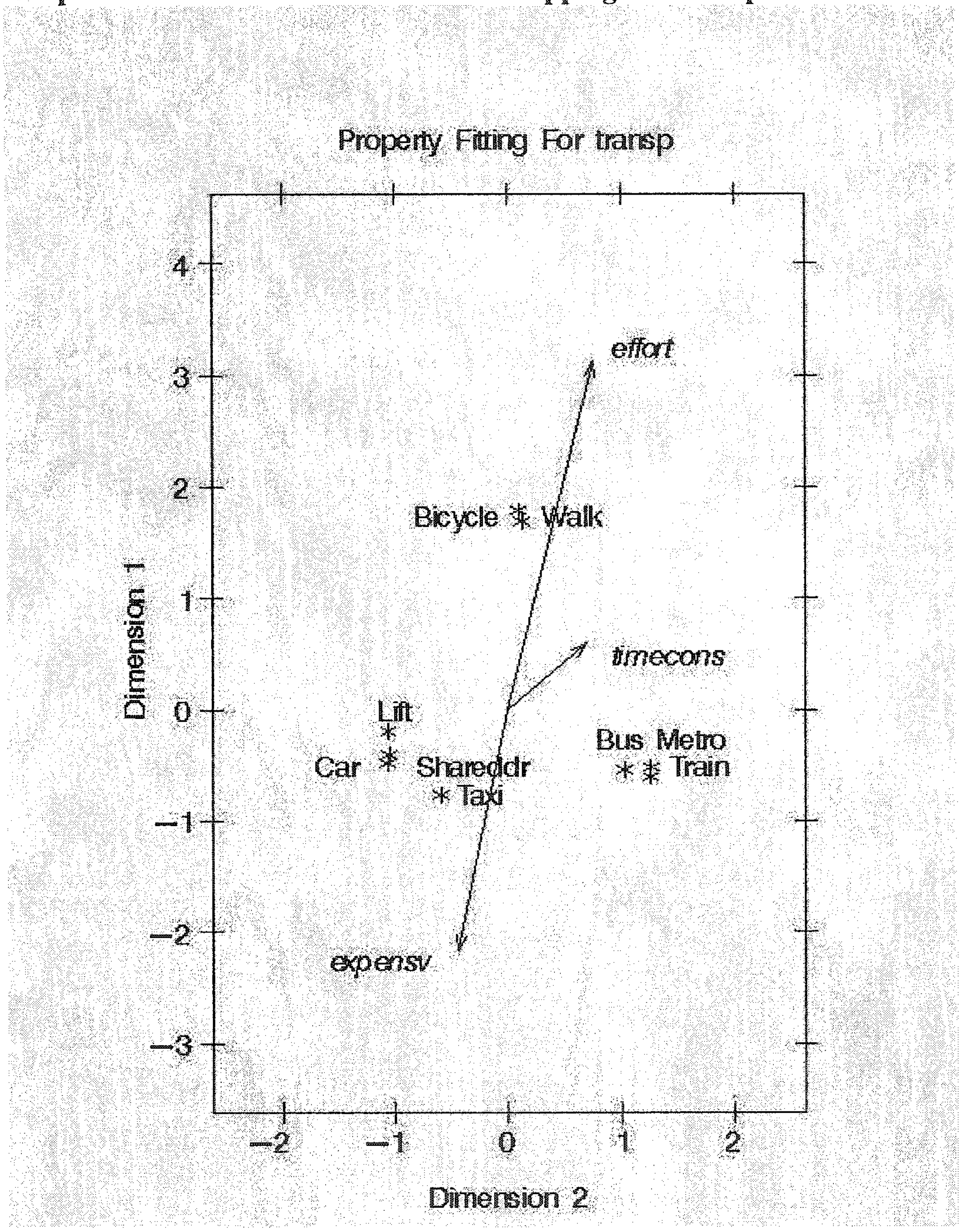


APPENDIX 13: STIMULUS SPACES OBTAINED FROM PREFERENCE JUDGEMENTS

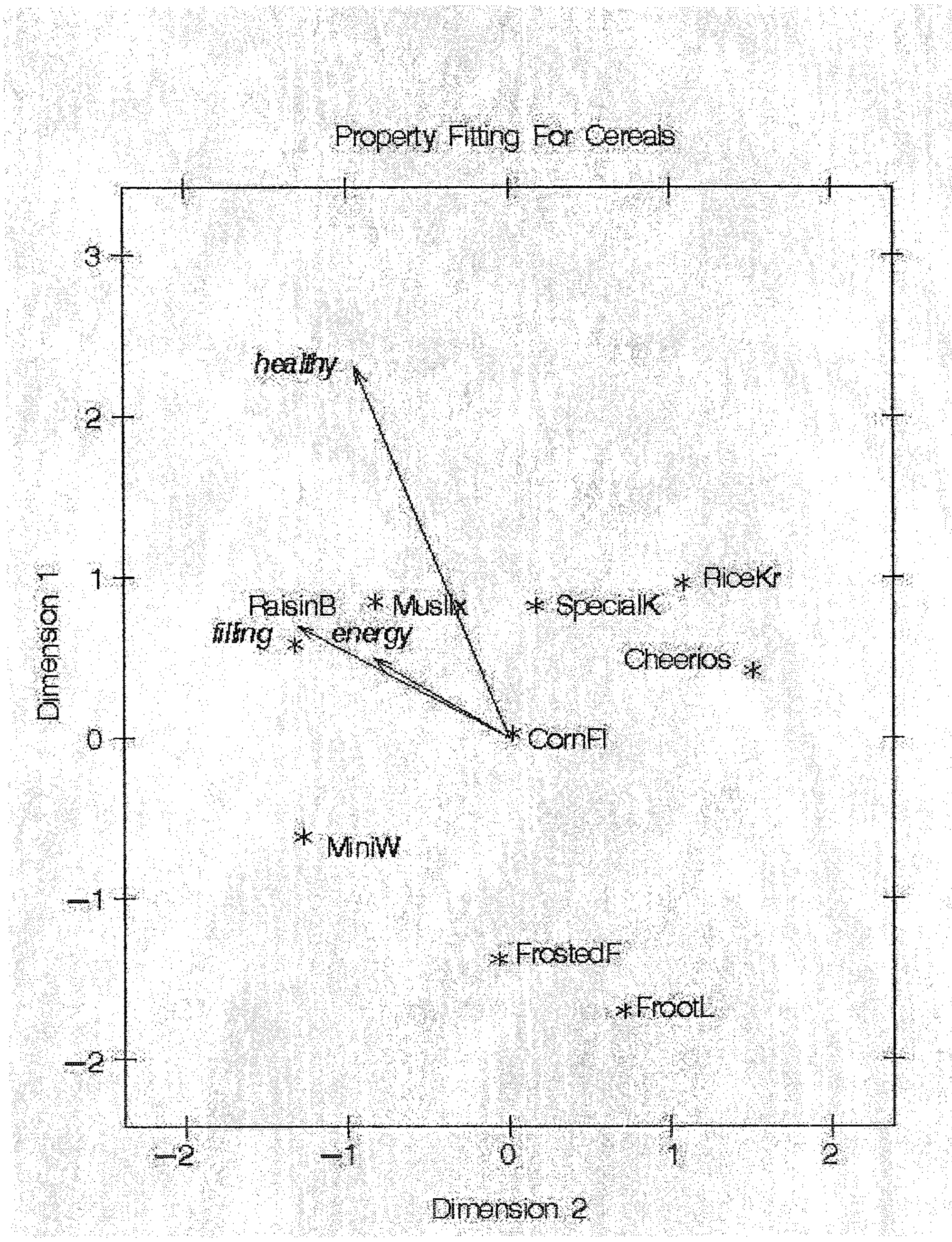
Graph 1: Two-Dimensional Preference Mapping for Fabrics



Graph 2: Two-Dimensional Preference Mapping for Transportation Modes



Graph 3: Two-Dimensional Preference Mapping for Brands of Cereals



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