An Experimental Study of
the Number of Levels Effect in Metric Conjoint Analysis

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ABSTRACT

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The purpose of this study is to investigate the "Number of Levels Effect" in metric conjoint analysis, which is observed whenever the estimated relative importance weight of an attribute included in a conjoint design depends on the number of levels along which it is defined. An experiment was conducted with 248 undergraduate students to provide additional evidence to the "Number of Levels Effect", and to investigate its relationship with several characteristics of a conjoint design: the number of attributes used to construct conjoint profiles, the number of response categories of the rating scale that respondents use to express their preferences, the nature of the attribute (i.e., discrete versus quasi continuous), and the relative importance of the attribute. The stimuli that were selected for the experiment were corded residential telephones. The results indicate that in metric conjoint analysis, the estimated relative importance of an attribute is a positive function of the number of levels along which it is defined. Also, the "Number of Levels Effect" exists both for quasi continuous and discrete attributes, and it does not depend on the number of response categories of the rating scale. Finally, the "Number of Levels Effect" is related to the number of attributes included in the design (for relatively unimportant attributes), and its magnitude is negatively related with the importance of an attribute. In order to minimize the "Number of Levels Effect" it is recommended to define when possible all attributes on a similar number of levels, or at least on a number of levels which is consistent with their self-reported importance.

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INTRODUCTION

Conjoint analysis refers to any decompositional method used to estimate the structure of consumers' preferences for product or service attributes, given their overall evaluations of a set of alternatives which are prespecified in terms of levels of the different attributes (Green and Srinivasan, 1978; 1990). Typically, the alternatives are generated by an experimental design that combines the levels of the different attributes as product or service profiles. After consumers express their relative preferences for different profiles, conjoint analysis decomposes overall evaluations collected from consumers to determine the relative value or part-worth of all levels of each attribute When the consumer evaluations are expressed on an interval scale, and ordinary least squares is used to estimate levels' part-worth, conjoint analysis reduces to the regression approach which is used extensively to study human information integration in psychology and management (Louviere, 1988).

Conjoint analysis is a very popular method to gain insight into consumers' preferences. Since its introduction to the marketing research community by Green and Rao (1971), researchers have kept developing and refining conjoint analysis related methodologies. Thus, several data collection methods, estimation procedures, stimuli or profiles presentation schemes, and software packages are available today to conjoint analysts.

Reviews of the professional applications suggest that conjoint analysis is currently used in a wide variety of research situations (Cattin, and Wittink, 1982; Wittink and Cattin, 1989). The main applications of conjoint analysis are new product development, competitive analysis, pricing, market segmentation, and repositioning. Based on a survey of the major research suppliers in the U.S., Wittink and Cattin (1989) estimate that a minimum of 200 commercial applications of conjoint analysis are conducted every year. Also, researchers increasingly make use of rating scales (instead of rank orders) in typical commercial applications Metric conjoint analysis of full-profile preference ratings now accounts for half of the commercial applications, as opposed to about a third in the 70's.

Conjoint analysis is also used to derive the part-worth or the importance weight of the attributes used to construct conjoint profiles. Also, researchers often estimate the *relative* importance weights of the attributes. The relative importance weight of an attribute is defined as the ratio of the difference in part-worth between the most and the least preferred levels for that attribute, to the sum of the differences in part-worths between the most and the least preferred levels for all attributes included in the conjoint design (Jain et al., 1979). Importance weights estimated through conjoint analysis allow researchers to identify determinant attributes, which are defined to be closely related to preference or to actual purchase decisions (Myers and Alpert, 1968). In fact, consumers use those important or determinant attributes to compare and evaluate brands within a product or service category (Alpert, 1971).

Until recently researchers usually assumed that estimated relative importance weights are comparable across attributes, even when attributes were defined on unequal number of levels. This assumption however was seriously questioned in several empirical studies (Creyer and Ross, 1988; Currim, Weinberg, and Wittink, 1981; Mishra, Umesh, and Stem, 1989; Reibstein, Bateson, and Boulding, 1988; Wittink and Krishnamurthi, 1981; Wittink, Krishnamurthi and Nutter, 1982; Wittink, Krishnamurthi and Reibstein, 1989; Wittink, 1990; Wittink, Huber, Fiedler, and Miller, 1992). In several instances, researchers concluded that the estimated relative importance weight of an attribute is in fact a positive function of the number of levels along which it is defined (i.e., the "number of levels effect": as the number of levels of an attribute increased, the estimated relative importance weight of that attribute also increased). Moreover, the number of levels effect seems to be rather generalizable. It was found to apply to various conjoint data collection and estimation methods.

The number of levels effect causes concern for the users of conjoint analysis. For example, if the practitioners believe that an attribute is relatively important and want to empirically examine this issue, they may include more levels for that attribute than others. If the number of levels effect exists as claimed in the literature, the expectations of the researchers will be confirmed simply as an artifact of the number of levels included in the study, even when the attribute of interest is relatively less important to the consumers. Therefore, marketing decisions will be biased in favour of the attributes that are defined along a higher number of levels.

Within this framework, the observed number of levels effect is a serious problem for conjoint analysts who would like to rely on estimated relative importance weights to identify determinant attributes. In their most recent review article on conjoint analysis, Green and Srinivasan (1990) call for research to isolate the cause(s) of the number of levels effect and for methods to minimize the problem.

A mathematical explanation of the number of levels effect was already suggested for non metric conjoint analysis of rank-order preference judgments (Wittink and Krishnamurthi, 1982; Wittink, Huber, Fiedler, and Miller, 1992). The number of levels effect was also evidenced in several studies involving the collection of preference judgments on rating scales. No explanation however is currently available for conjoint analysis of full-profile ratings, though it is the most popular conjoint analysis method in commercial settings (Wittink and Cattin, 1989).

This study is an attempt to address several issues related to the number of levels effect in metric conjoint analysis of full-profile ratings and examines how generalizable the effect is by investigating the possible relationships between the number of levels and several characteristics of the conjoint design. The overall purpose of the study is to elaborate recommendations for users who would like to rely on conjoint analysis results to estimate the importance weights of the attributes in the conjoint design. Thus, specific recommendations to correct or minimize the number of levels effect in full-profile rating tasks are presented in this study.

SECTION 2

LITERATURE REVIEW

In a typical conjoint analysis, the researcher usually begins with the definition of the product or service of interest along several relevant attributes which are determinant in affecting consumers' preferences (Green and Srinivasan, 1978). For instance, a corded residential telephone could be defined in terms of design, color, price, manufacturer, etc. Also, for each attribute the researcher specifies possible levels, that are merely instances of an attribute. Attributes or factors may be essentially discrete such as brand name (with attribute levels such as AT&T, Northern Telecom, etc.), or quasi continuous (i.e., discretisized continuous) such as price. Conjoint analysis then involves the collection of preference judgments for an appropriate set of conjoint profiles (i.e., combinations of factor levels) from a sample of consumers. The preference judgments may be collected from respondents on a rating scale (e.g., likelihood of purchase, liking, etc.), or alternatively, respondents may be asked to rank order conjoint profiles in terms of overall preference (Green and Srinivasan, 1978; 1990).

One of the objectives of conjoint analysis is to estimate the part-worth or the utility of all levels of each factor for a given respondent, so that his/her tradeoffs between the levels of the different factors can be better understood. This is achieved by decomposing a respondent's overall preference judgments of conjoint profiles into utility estimates or part-worths for all levels of each factor. Estimated part-worths are typically used for predicting consumer reactions to planned changes in product or service design by adding the relevant part-worths for all attributes.

The identification of attributes which are important in influencing product or service preferences is another objective of conjoint analysis. The part-worth or importance of an attribute is usually defined in terms of the range in utility estimates of that attribute, that is the difference between the most and the least desirable levels of that attribute (Jain, Acito, Malhotra, and Mahajan, 1979). In order to ascertain the importance of an attribute with respect to other attributes and across respondents, researchers often compute its relative importance weight by dividing the respondent's utility range for that attribute by the sum of the utility ranges for all attributes for that respondent (Jain, Acito, Malhotra, and Mahajan, 1979).

THE "NUMBER OF LEVELS EFFECT" IN CONJOINT ANALYSIS

Definition of the "Number of Levels Effect"

Until recently, it was implicitly assumed by researchers that estimated relative importance weights of attributes defined on unequal number of levels were comparable across attributes. In other words, the estimated part-worth of an attribute was considered to be independent of the number of levels along which it was defined. Several recent empirical studies, however, concluded that the estimated part-worths are a positive function of the number of levels used to define attributes (Creyer and Ross, 1988; Currim, Weinberg, and Wittink, 1981; Mishra, Umesh, and Stem, 1989; Reibstein, Bateson, and Boulding, 1988; Wittink and Krishnamurthi, 1981; Wittink, Krishnamurthi and Nutter, 1982; Wittink, Krishnamurthi and Reibstein, 1990; Wittink, 1990; Wittink, Huber, Fiedler, and Miller, 1992). As summarized in Table 1, most of these studies indicate that keeping the end points (i.e., the "extreme" levels in terms of utilities) of an attribute constant, the addition of intermediate levels to the conjoint design increases the estimated part-worth of that attribute to the consumer, both under conjoint ranking and rating tasks.

These results cause concern for the users of conjoint analysis, because estimated part-worths should be theoretically independent of the number of levels used in a conjoint design (Green and Srinivasan, 1990). Also, if the estimated part-worths are indeed a function of the number of levels, then one should question the comparability of part-worths across attributes with unequal number of levels. Thus, the notion of the relative importance weight of an attribute, which is of primary interest to researchers and practitioners who rely on conjoint analysis results would become meaningless.

Previous Studies on the "Number of Levels Effect"

Currim, Weinberg, and Wittink (1981) were the first to report the number of levels effect in the literature. They conducted a conjoint study the purpose of which was to define a new subscription program for a performing arts series. They collected from each of the 306 subscribers who participated in their survey paired comparison judgments for programs defined on two attributes at a time. The six attributes they included in their survey were: price, discount percentage on subscriptions, renown of the performers, driving time to the auditorium, number of events offered in a subscription series, and subscription seating priority. Among the six attributes, three were defined on three levels, and the remaining three were defined on two levels only. Part-worths were estimated by ordinary least squares (OLS) analysis of preference rank orders.

They found that attributes which were defined on three levels all ranked higher in terms of average estimated importance than those defined on two levels only. The derived importance weight for the attributes defined on two levels varied across respondents from a minimum of 0.2 to a maximum of 0.6. For the attributes with three levels, the minimum was 0.4 and the maximum was 0.8. The authors argued that these results could be due to three main reasons: "managerial", "psychological", or "mathematical". They concluded that direct comparisons between the importance weights of the attributes could be made only when attributes are defined on an equal number of levels.

To examine the replicability of these findings Wittink, Krishnamurthi, and Nutter (1981; 1982) conducted an experiment with 161 first year MBA students. The purpose of the study was to systematically assess the unexpected relationship between the number of levels used to define an attribute and the estimated relative importance weight of that attribute. The stimuli involved in the experiment were summer jobs defined in terms of type of activity, location, salary, and people in the organization In their study, two attributes which were selected as experimental treatments were defined either on two or four levels. For instance, the levels for salary included either \$1,200, \$1,600, \$2,000, or \$2,400, or were limited to \$1,200, and \$2,400. Therefore, the range of variation in the levels for price was held constant across treatments while the number of levels varied They also manipulated the data collection method. For each subject, they collected either preference ratings for 16 full-profiles of summer jobs, or tradeoff judgments involving paired comparisons between combinations of attribute levels. The part-worths were estimated by LINMAP (Srinivasan and Shocker, 1973), a conjoint analysis model and software which can accommodate both full-profile and tradeoff judgments.

Under both data collection procedures, they found that the estimated importance weights were not comparable across attributes with unequal number of levels. For instance, salary was first in terms of average relative importance in those treatments where it was defined on four levels. However, it was second or third in terms of importance when defined on two levels only. Specifically, the average estimated relative importance weight of salary was 0.41 when defined on four levels and 0.23 when defined on two levels although the range of variation in levels was constant in both conditions Thus, the observed reversal in the average rank order for the manipulated attributes confirmed the findings of the previous study.

Building on Parducci's Range-Frequency theory of context effects, Creyer and Ross (1988) conducted an experimental study to account for the effect of both the range of levels on which the attributes are defined and the number of levels used to define attributes on the estimated relative importance weights. In their study, 136 undergraduate university students rated on a 7-point scale 32 full-profiles of cars which were defined on the following attributes: country of origin, body style, transmission, top speed, price, wheel size, and miles per gallon. The students also provided on a 100-point rating scale self-explicated importance weights for the seven attributes of the design. The number of levels was manipulated by defining miles per gallon either on four levels (i.e., 25 Mpg, 30 Mpg, 35 Mpg, 40 Mpg), or two levels (i.e., 25 Mpg, 40 Mpg). They estimated a relative importance weight for each attribute by OLS regression of each subject's ratings of the constructed profiles.

In general, the hypothesis regarding the number of levels effect was supported. The average estimated relative importance weight for the manipulated attribute (i.e., miles per gallon) was 0.147 when defined on four levels, and 0.107 when defined on two levels only (i.e., a 35% difference in average importance). Again, this study suggests that it is inappropriate to compare the estimated relative importance weights of attributes when attributes are defined on unequal number of levels. Furthermore, it shows that this problem also extends to conjoint analysis situations in which ordinary least squares is used to estimate part-worths.

Mishra, Umesh, and Stern (1989) conducted a Monté Carlo simulation the general purpose of which was to investigate the influence of several factors on both the bias and the precision of estimated importance weights in conjoint analysis. Specifically, they investigated the effect on the estimated importance weights of several factors: the estimation method used in conjoint analysis (i.e., LINMAP, MONANOVA, and OLS), the amount of judgmental error (i.e., the difference between the subjects "true" preferences and their estimated preferences), the number of levels used to define the attributes, the number of attributes, and the number of profiles involved in the conjoint design. They found that

OLS was performing somewhat better than both MONANOVA and LINMAP in terms of precision, which was defined for each attribute as the ratio of the standard deviation of its importance weight to the magnitude of its importance weight (precision indices computed for each attribute were averaged across all attributes to form an overall index). Also, they observed that the estimated importance weights for the attributes defined on two levels were downward biased and upward biased for attributes defined on three levels Their results showed that for most estimation procedures used in conjoint studies, the estimated relative importance weight of an attribute increases as the number of levels on which it is defined increases. These findings suggest that the estimation method which is used is a potential contributor to the number of levels effect.

Based on a study conducted by Reibstein, Bateson, and Boulding (1988), Wittink, Krishnamurthi, and Reibstein (1989) provided further insight into the number of levels effect. The overall objective of Reibstein et al.'s experimental study was to evaluate and compare the reliability of different conjoint analysis methods Specifically, they attempted to compare alternative data collection methods (i.e., trade-off matrix method, full-profile method, and paired profile comparisons method) in terms of various reliability measures (i.e., reliability over stimulus set and reliability over attribute). Also, they looked at the effect of the number of levels used to define an attribute on the reliability of conjoint analysis results. Their study involved five different product categories across three different product/service classes (durable, nondurable, and service). The five products were defined on six attributes, and for each product/service they manipulated the relevant price either on three or five levels, keeping the range of variation in levels constant OLS regression of the preference judgments was used to estimate the part-worths.

Wittink, Krishnamurthi, and Reibstein (1989) report the results of Reibstein et al.'s study regarding the number of levels effect. They found that for all three data collection methods which were involved in the study, the average estimated relative importance of price was significantly higher when the attribute was defined on five levels than when it was defined on three levels only. Based on their estimated regression coefficients, they found that, on average, the relative importance of price was 7% higher when it was defined on four levels. The authors concluded that the number of levels effect is a rather general effect. It is not limited to the trade-off matrix method, but it extends also to the full-profile rating method. They also noted that the number of levels effect exists no matter the product category for which conjoint analysis is conducted.

In a review of the literature on the number of levels effect, Wittink (1990) suggests that alternative data collection methods such as Adaptive Conjoint Analysis (Johnson, 1974; 1991), or Hybrid Conjoint Analysis (Green, Goldberg, Montemayor, 1981; Green, 1984) could provide some solutions to the observed number of levels effect. In Adaptive Conjoint Analysis as in Hybrid Conjoint Analysis part-worths are estimated based on both self-explicated importance weights and the decomposition of trade-off or full-profile preference judgments. This may minimize the observed number of levels effect.

Following Wittink's (1990) suggestions, Wittink, Huber, Fiedler, and Miller (1992) conducted a large scale experimental study to assess whether the number of levels effect would also occur in Adaptive Conjoint Analysis. The stimuli they selected were refrigerators which were defined either on nine or five attributes (i.e., brand name, capacity, energy cost, compressor noise, price, design, warranty, type of refrigerant, and dispenser). For each subject, they estimated relative importance weights derived from two data collection methods: full-profile preference judgments, and Adaptive Conjoint Analysis. They also manipulated the order of the conjoint task (full-profile versus ACA), the number of attributes used to construct the stimuli, the number of levels used to define the attributes, and the order of the attributes within the stimuli. For the full-profile method, preference judgments where collected on a 9-point probability of purchase rating scale (i.e., 10% chance or less, 20% chance, etc.).

The number of levels was the most significant of all the experimental manipulations For each of the four manipulated attributes, using four levels instead of two led to significantly higher estimated relative importance weights. As expected, the comparison of the number of levels effect between the two data collection methods involved in the study showed that the observed effect is greater in the full-profile method than in Adaptive Conjoint Analysis. Also, though not significant, the results showed that the smaller the average self-explicated importance, the larger the number of levels effect.

Possible explanations for the "Number of Levels Effect"

When Currim, Weinberg, and Wittink (1981) first observed the number of levels effect, they suggested that it could be due to three main reasons: "managerial" (managers for whom a conjoint study is intended may be tempted to define an attribute that is seen as more important on more levels), "psychological" (respondents consciously or unconsciously react to the number of levels by weighting more heavily an attribute defined on a higher number of levels), or "mathematical" (the procedure used for estimating the part-worths -based on which the importance weights are computed- are such that importance weights increase as the number of levels increases).

A mathematical explanation of the number of levels effect was suggested by Wittink and Krishnamurthi (1982), and Wittink, Huber, Fiedler, and Miller, (1992) for rank order preference judgments and when part-worths are estimated by OLS. Mathematically, Wittink and Krishnamurthi (1982) showed that the derived relative importance weight of an attribute increases as the number of levels used to define that attribute increases, if one assumes that the stimuli are evaluated consistently with a lexicographic process (i.e., the subject examines the profiles in terms of the most important attribute, and then breaks the ties by examining the attribute that ranks second in terms of importance, etc.). Also, as presented in Appendix 1, it can be shown that for ranking tasks and when OLS is used, both the maximum and the minimum values that the relative importance weights of an attribute can achieve are mathematically constrained.

Researchers were unable to provide a similar explanation for conjoint rating tasks, though a similar number of levels effect was observed across several empirical studies. It was argued, however, that under conjoint rating tasks respondents provide in fact rank-order like preferences, and that rating scale values may not be better than an ordinal measurement (Wittink, Huber, Fiedler, and Miller, 1992). Some support to this is provided by Parducci's Range-Frequency theory (Parducci, 1965; 1981). Parducci's frequency effect states that when respondents use a rating scale, they have a tendency to use each available response category with an equal frequency. If under rating tasks, respondents have a tendency to spread values across the scale somewhat equally, then it is possible that the rating scale values do not, as it is usually assumed, have interval but rather ordinal properties. Thus, the mathematical explanation provided for ranking tasks may also apply to conjoint analysis of full-profile preference ratings (Wittink et al., 1992).

Another possible explanation is that the effect is due to respondents reacting to the conjoint design. Respondents may pay more attention to an attribute, relative to other attributes, as the number of levels used for this attribute increases (Wittink, Huber, Fiedler, and Miller, 1992). Though plausible, this hypothesis has never been tested. The observed number of levels effect may also be explained by a combination of these mathematical and psychological reasons.

HYPOTHESES

As the literature which is reviewed above suggests, there is strong evidence regarding the number of levels effect across various conjoint data collection methods, estimation procedures, and types of stimuli: OLS estimation of paired comparison judgments (Currim, Weinberg, and Wittink, 1981), LINMAP estimation of full-profile and tradeoff judgments (Wittink, Krishnamurthi, and Nutter, 1982); OLS estimation of full-profile judgments (Creyer and Ross, 1982); LINMAP, MONANOVA, and OLS estimation of preference judgments (Mishra, Umesh, and Stern, 1989); OLS estimation of full-profile, trade-off, and paired comparison judgments (Wittink, Krishnamurthi, and Reibstein, 1989); and OLS and ACA estimation of full-profile judgments (Wittink, Huber, Fiedler, and Miller, 1992)

In the light of the above literature, a set of hypotheses are stated regarding the conditions under which the number of levels effect is expected to be observed. Since metric conjoint analysis of full-profile ratings is the currently most popular approach to conjoint measurement in commercial applications (Wittink and Cattin, 1989), the focus of the hypotheses is limited to such settings.

The first hypothesis of the study simply expresses that the number of levels effect, which as been observed for various conjoint tasks and estimation methods, will be observed for metric conjoint analysis of full-profile rating tasks.

Hypothesis 1: In metric conjoint analysis of full-profile ratings, the estimated relative importance weight of an attribute increases as the number of intermediate levels used to define that attribute increases.

The number of levels effect has been almost exclusively reported in the literature for quasi continuous (i.e., discretisized continuous) attributes such as miles per gallon or price. Thus the issue whether the number of levels effect might also occur with discrete attributes remains unexplored. There is no theoretical reason to believe, however, that the mathematical explanation for the number of levels effect in conjoint rank orders would not apply to discrete attributes. Also, the psychological factors which might cause the number of levels effect might be expected to operate for discrete attributes as well as quasi continuous attributes. Therefore, the following hypothesis can be stated.

Hypothesis 2: In metric conjoint analysis of full-profile ratings, the number of levels effect exists for quasi continuous as well as discrete attributes.

As suggested by Wittink, Krishnamurthi, and Reibstein (1989), Wittink (1990), and Wittink, Huber, Fiedler, and Miller (1992), the number of levels effect in full-profile rating tasks may be dependent on the number of response categories of the rating scale available to respondents. The authors argue that in full-profile rating tasks respondents actually express rank-order like preferences, and that ratings may have ordinal rather than interval properties. Thus, the mathematical explanation provided by Wittink and Krishnamurthi (1982), and Wittink, Huber, Fiedler, and Miller, (1992) may also apply to full-profile ratings. The authors suggest that rating scales with larger number of response categories may reduce the number of levels effect.

This negative relationship between the number of levels effect and the number of response categories may be more pronounced when the number of profiles in a conjoint design is high than when it is low. For example, Louviere (1988) suggests that an 11-point rating scale should be selected if there are 16 or fewer stimuli, and a 21-point scale should be selected for designs with more stimuli because rating scales with larger number of response categories allow respondents to better discriminate between conjoint profiles. Similarly, Cox (1980) and Morison (1972) state that the channel capacity of a scale (i.e., the amount of information which is available from respondents that a scale captures) increases with the number of response categories. Despite these theoretical arguments, surprisingly no empirical investigation of the number of levels effect across conjoint rating tasks that differ in terms of the number of response categories has been reported in the literature. Therefore, it is hypothesized that the number of levels effect is less pronounced for rating scales that have a larger number of response categories.

Hypothesis 3: In metric conjoint analysis of full-profile ratings, the number of levels effect is less pronounced for rating scales that have a larger number of response categories.

Another variable of interest with regard to the number of levels effect is the perceived importance of the manipulated attributes in the conjoint design. It can be argued that the subjects will pay more attention to the attributes they perceive to be relatively more important. If, however, the number of levels is larger for the relatively unimportant attributes than for the important ones, such variation across the profiles of the conjoint design may encourage the respondents to pay more attention to the relatively unimportant attributes than they would otherwise. Consequently, it is expected that an increase in the number of levels will increase the subjects' attention to the relatively unimportant attributes more than it does to important attributes. It should be noted that this hypothesis assumes that those attributes which are perceived to be important by subjects will be examined carefully, regardless of the number of levels for those attributes. An increase variation, however, along relatively unimportant attributes will draw more attention to them. It is hypothesized that the number of levels effect is less pronounced when the number of levels vary along a relatively important attribute than a relatively unimportant attribute.

Hypothesis 4: In metric conjoint analysis of full-profile ratings, the number of levels effect is less pronounced when the number of levels vary along a relatively important attribute than a relatively unimportant attribute.

A final variable which is potentially related to the number of levels effect is the number of attributes in a conjoint design. Since a full-profile conjoint task presents product/service profiles one after another and requests the subjects to respond to the changes in the profiles, the task itself invites the subjects to pay attention especially to those attributes along which there are more variations. All else being equal, such variations are likely to be more noticeable when the number of attributes is small than when it is large. Wittink, Huber, Fiedler, and Miller's (1992) findings partially confirm such an effect. Among the four attributes they manipulated the estimated relative importance weight of an attribute was significantly related to the number of attributes used in the design. This attribute was the least important of the four attributes they manipulated.

Huber, Wittink, Fiedler, and Miller (1993) suggest that under repetitive stimuli rating tasks such as full-profile conjoint tasks, where stimuli are defined on many attributes, subjects tend to rely more heavily on a limited set of key attributes when expressing their preferences. Thus, respondents may be more sensitive to the variations in number of levels of an attribute when conjoint stimuli are defined only along a few numbers of attributes (i.e., five or less attributes). Therefore, it is hypothesized, that the number of levels effect is more pronounced when stimuli are defined on a small number of attributes.

Hypothesis 5: In metric conjoint analysis of full-profile ratings, the number of levels effect is less pronounced when the number of attributes used to define conjoint profiles is large than when it is small.

SECTION 3

METHODOLOGY

OVERVIEW

An experiment was conducted to test the proposed hypotheses. A full factorial design was generated with the following five factors with two levels each: the number of attributes with which conjoint profiles are constructed (5 versus 9 attributes), the number of response categories for the rating scale the respondents used to express their preferences (7-point versus 11-point rating scale), the nature of the attribute (quasi continuous versus discrete attribute), and the relative importance of the attribute (relatively high versus relatively low importance) along which the number of levels was manipulated (2 versus 4 levels). As summarized in Figure 1, the design has $2^5 = 32$ experimental cells.

In order to implement this experiment, a product category, corded residential telephones, was selected. Then, the relevant attributes along which the product could be defined were identified based on a review of promotion material available from several manufacturers, an interview with an expert, and a pretest with a sample of subjects. The selection of the final attributes to construct the conjoint profiles was based on the manipulations implied by the experimental design as presented in Figure 1.

The number of levels (i.e., 2 versus 4 levels) of four attributes was manipulated. Among these four attributes, two were discrete (important and unimportant attribute), and the two others were quasi continuous (important and unimportant attribute). Within each experimental cell, conjoint profiles for the conjoint rating task were developed from an orthogonal, main effects, fractional design.

Subjects who completed the paper and pencil conjoint task were 248 undergraduate commerce students at Concordia University. Subjects were instructed to express their preferences for several full conjoint profiles on a probability of purchase rating scale Also, for manipulation check purposes, self-explicated importance weights were collected for each of the four manipulated attributes on a 100-point constant-sum scale.

SURVEY INSTRUMENT DESIGN

Selection of a product category

The product category that was selected for the experiment was corded residential telephones. Other product categories which were used in conjoint experiments involving students include cars, summer jobs, pocket calculators, etc. It was assumed that corded residential telephones would be appropriate, mainly because subjects were likely to be very familiar with that product category. As suggested by Kumar and Gaeth (1991), product familiarity in conjoint analysis is related to possible attribute order effects (i.e., the estimated part-worth of an attribute is a positive function of its rank order in the conjoint profiles). Thus, the selection of a product category with which subjects were familiar presumably helped to limit any possible attribute order effect.

Selection of important attributes and their levels

Relevant telephone attributes or features with which conjoint profiles were constructed were identified by following the suggestions in the literature (Green and Srinivasan, 1978). Promotion material available from a telephone service provider and six major residential telephone manufacturers distributing their products in Canada were reviewed (i.e., Bell Canada, Northern Telecom, AT&T, Panasonic, General Electric, Telemax, Conair Consumer Products). Based on that review, an initial list of thirty telephone attributes was generated. An expert from Northern Telecom then reviewed the initial list, and selected twenty two attributes for a pretest with a sample of students.

The objective of the first survey instrument which is presented in Appendix 2 was to determine the relative perceived importance of the twenty two attributes selected by the expert. In the pretest, subjects were asked to evaluate the importance of the twenty two attributes using a 7-point importance rating scale. Also, subjects provided self-explicated preferences for the brand, colour, country of origin, and the size of dial buttons of corded telephones. As suggested by Griffin and Hauser (1993), self-reported preferences were collected on a 9-point desirability scale anchored by 9 (i.e., very desirable).

The experimenter distributed 116 questionnaires to a convenience sample of undergraduate commerce students within three classes at Concordia University. The subjects were instructed to self administer the questionnaire, and return it to the experimenter a week after its distribution. Within each class, subjects were also promised that a lottery would be organized for those who complete their questionnaire, and that two prizes of $20 each would be distributed for their participation.

For the pretest, 65 usable questionnaires were completed, giving a response rate of 56%. The average self-reported importances and standard deviations for the 22 attributes included in the pretest are presented in Table 2. The average self-reported preferences for the selected levels of brand, colour, country of origin, and dial button's size are presented in Table 3.

The selection of the attributes for the construction of the conjoint profiles was based on two considerations. First, the attributes selected should be considered as relatively important (i.e., determinant in making a purchase decision). Also, they should allow manipulations implied by the experimental design both in terms of the nature of the attribute (i.e., discrete versus continuous), and relative importance of the attribute (i.e., relatively important versus relatively unimportant).

Based on the results provided in Table 2, the price (μ=5.86, σ=1.26) and the memory of the telephone for frequently dialed numbers (μ=4.86, σ=1.48) were selected as respectively relatively important and relatively unimportant quasi-continuous attributes. The colour (μ=5.31, σ=1.30) and the country of origin (μ=3.35, σ=1.79) of the telephone were selected as respectively relatively important and relatively unimportant discrete attributes.

The other attributes which were included in the conjoint design were the design of the telephone (μ=5.40, σ=1.36), whether the telephone has a one-touch redial button (μ=4.33, σ=1.55), whether the telephone has emergency buttons (μ=4.91, σ=1.55), the length of the warranty (μ=5.33, σ=1.40), and whether the telephone has a ringer volume control button (μ=5.74, σ=1.21).

The levels of the discrete attributes that were used to construct conjoint profiles were selected so that they could allow experimental manipulations in terms of number of levels, and also their mean importance ratings were far enough apart to be considered distinct (Green and Srinivasan, 1978). Based on the results presented in Table 3, black (μ=7.61, σ=2.30), ivory (μ=6.42, σ=2.98), blue (μ=4.55, σ=2.32), and red (μ=3.58, σ=2.06) were the levels selected for the colour of the telephone. Canada (μ=7.73, σ=1.34), Japan (μ=7.47, σ=1.69), USA (μ= 7.04, σ=1.88), and Taiwan (μ=5.03, σ=1.56) were selected for the country of origin. The levels of the quasi continuous attributes were $40, $55, $70, and $85 for the price, and 5, 10, 15, 20 telephone numbers for the memory.

The final list of attributes and their associated levels are presented in Table 4. The table also indicates which levels were used when a manipulated attribute (i.e., colour, country, price, and memory) was defined on two levels only. Generally, these levels were the "extreme" levels (i.e., for the discrete attributes, the least and the most preferred levels as indicated by the results of the pretest). For the quasi continuous attributes, it was assumed that subjects' preferences would be either a positive or a negative function of the number of levels. For price, a negative relationship with overall preferences was assumed. Therefore, a telephone priced at $40 was expected to be preferred to a telephone priced at $55. For memory, a positive relationship with overall preferences was assumed, a telephone with 20 memorized numbers being preferred to one with 5 memorized numbers. These "extreme" levels of the associated attributes which define the ranges of the attribute levels were kept as constant as possible across all experimental cells.

It should be noted that neither colour and price, nor country and memory were significantly different in terms of importance. Thus, as the experiment was designed, meaningful comparisons in terms of relative importance between the four manipulated attributes are possible only across attributes of the same nature (i.e., discrete versus quasi continous).

Construction of conjoint profiles

Within each experimental cell, conjoint profiles were developed from an orthogonal, main effects, fractional design (Addelman, 1962; Green, Caroll, and Carmone, 1978). Within cells where a manipulated attribute was defined on 2 levels, the "extreme" levels for that attribute were used. For instance, black and red were used for colour, Canada and Taiwan were used for the country of origin. In experimental cells where conjoint profiles were constructed with 5 attributes, the four manipulated attributes and the ringer volume control button attribute made up the list of attributes. When conjoint profiles were constructed with 9 attributes, all of the attributes which were selected after the pretest were included in the conjoint design, as indicated in Table 4.

The number of profiles which were generated within each experimental cell was either 6 (5 attributes all defined on 2 levels), 8 (4 attributes all defined on 2 levels and one attribute defined on 4 levels), 12 (9 attributes all defined on 2 levels), or 16 (8 attributes all defined on 2 levels and one attribute defined on 4 levels), depending on the number of attributes and the number of levels of the four manipulated attributes. Also, 7 additional conjoint profiles were generated within each experimental cell, to be used as hold out sample for predictive validity check. Finally, the attributes within conjoint profiles were randomly rank ordered (Kumar and Gaeth, 1991). The obtained rank order of the attributes was then kept consistent across all profiles, and across all experimental cells.

CONJOINT TASK

The conjoint task was a paper and pencil task for all subjects. After reading some instructions, respondents expressed their preferences on either a 7-point or an 11-point probability of purchase scale (*"How likely would you be to consider the above* [product description] *as a possible corded residential telephone for yourself if you were purchasing a corded residential telephone today?"*). Within experimental cells where the response scale was a 7-point rating scale, scale values were defined as: no chance (0), slight possibility (1), some possibility (2), fairly good possibility (3), ..., up to certain (6). In cells where the response scale was defined on 11 points, intermediate descriptions were added (please refer to Appendix 3).

Also, self-explicated importance weights were collected for manipulation check purposes as presented at the end of Appendix 3. Following the recommendations by Srinivasan (1988), subjects were asked to divide 100 points between four changes from the least to the most desirable level of each manipulated attribute (e.g., decreasing the price of the telephone from $85 to $40).

PROCEDURE

The experimenter distributed 487 questionnaires to a sample of undergraduate commerce students within twelve randomly selected classes at Concordia University. The subjects were instructed to self administer the questionnaire, and to return it to the experimenter a week after it was distributed.

Within each class, subjects were also promised that a lottery would be organized for those who complete their questionnaire, and that two prizes of $20 each would be distributed for their participation.

SECTION 4

RESULTS

ESTIMATION OF THE PART-WORTHS FUNCTION MODELS

Out of the 487 questionnaires that were distributed to the students, 267 usable questionnaires were collected a week after they were distributed (i.e., a response rate of 55%). For each subject, the following part-worths function model was estimated by ordinary least squares (see, for example, Jain et al., 1979):

$$S_p = \sum_{1}^{t} \sum_{1}^{m} \alpha_{ij} x_{ij}$$

Where:

S_p is the overall utility of the pth conjoint profile,

i denotes the attribute number (i=1,2, ..., t),

j denotes the level number (j=1,2, ..., m),

α_{ij} is the part-worth of the jth level of the ith attribute,

x_{ij} denotes the status (i.e., present or absent) of jth level of the ith attribute

Also, for each subject the Pearson's product moment correlation coefficient between the preference ratings for the seven holdout conjoint profiles and the preferences as predicted by the part-worths function model was computed. This correlation coefficient has been used as an estimate of the predictive validity of the part-worths function model for a given respondent (Green and Srinivasan, 1978). Nineteen subjects whose Pearson's correlation coefficient was extremely low ($\rho<.3$, and $p>.2$) were discarded from the sample. A very low correlation coefficient indicates that the part-worths function model poorly fits the preferences collected from a respondent. A poor prediction may be explained by the inadequacy of the model to represent the structure of the respondent's preferences, or merely a lack of interest on the part of the respondent in the conjoint task. The following analysis is based on the remaining sample of 248 subjects.

COMPUTATION OF THE RELATIVE IMPORTANCE WEIGHTS

Each subject had either 5 or 9 relative importance weights, depending on the experimental cell to which he/she belonged. The relative importance weight of an attribute is defined here as the ratio of the difference in utilities between the most and the least preferred levels for that attribute, to the sum of the differences in utilities between the most and the least preferred levels for all attributes. This can be expressed as follows (Jain et al., 1979; Wittink et al., 1992):

$$RIMP_i = (Max_i - Min_i) \,/\, \sum_{1}^{t} (Max_k - Min_k), \; k=1,2, \ldots, t$$

Where:

$RIMP_i$ is the relative importance of the ith attribute, (Σ $RIMP_i$=100),
i de 'otes the attribute number (i=1,2, ..., t),
Max_i is the largest utility (i.e., part-worth) of the ith attribute,
Min_i is the smallest utility (i.e., part-worth) of the ith attribute.

As suggested by Wittink et al. (1992), the set of estimated relative importance weights of subjects who evaluated conjoint profiles defined on 9 attributes was rescaled. When subjects rated conjoint profiles defined on 9 attributes, the estimated relative importance weight of the four manipulated attributes (i.e., colour, country, price, and memory) as well as the ringer volume control attribute were adjusted so that the sum of their relative importance weights equals to 100. Thus, the resulting set of adjusted relative importance weights was comparable to the set of estimated relative importance weights of subjects who evaluated conjoint profiles constructed with 5 attributes.

MANIPULATION CHECK

The purpose of the manipulation check is to verify that the mean relative importance ratings of the four manipulated attributes based on the pretest are in agreement with the mean self-explicated importance ratings obtained from the subjects of the experiment. As mentioned above and summarized in Table 2, the manipulation of the relative importance of attributes was based on the mean importance ratings of the 22 original product attributes. The colour and price of the telephone were identified as relatively important, and the country of origin and memory were selected as unimportant attributes for discrete and quasi continuous attributes respectively. The difference in the mean self-explicated importance ratings of the experimental subjects (please refer to the last question of the questionnaire in Appendix 3) parallel the differences in the means for the pretest.

In terms of the self-explicated importance, the price is the most important attribute (μ_{price}=45.53, σ=24.58), followed by colour (μ_{colour}=30.74, σ=26.43), country of origin ($\mu_{country}$=26.09, σ=26.34), and memory (μ_{memory}=21.77, σ=25.03), as presented in Table 6.

A paired t-test indicates that the difference in means between the self-explicated importance of price and memory is significant [μ_{price}-μ_{memory}=23.76, t(247)=10.45, p<.000]. Similarly, the difference in the means between the self-explicated importance of colour and country of origin is also significant [μ_{colour}-$\mu_{country}$=4.65, t(247)=2.81, p<.005].

HYPOTHESIS TESTING

The average estimated relative importance weights for the four manipulated attributes across experimental cells are presented in Table 5. Since treatments 3, 5, and 7 did not differ from treatment 1 with respect to the experimental manipulations, the average estimated relative importance weights for the four manipulated attributes in those treatments were aggregated with the relative importance weights of the four attributes in treatment 1. Similarly, the estimated relative importance weights of the four manipulated attributes in treatments 11, 13, 15, and 19, 21, 23, as well as 27, 29, 31 were aggregated with relative importance weights in treatments 9, 17, and 25 respectively. The rank order of each attribute in terms of estimated relative importance within each cell is also provided.

Across all cells, the price is the most important attribute (μ_{price}=28.55, σ=19.95), followed by colour (μ_{colour}=23.75, σ=18.52), country of origin ($\mu_{country}$=17.75, σ=13.91), and memory (μ_{memory}=13.59, σ=10.99). It should be noted that the rank order of these attributes in terms of estimated relative importance weight is the same as for self-explicated ratings mentioned in the previous section.

However, rank orders of the four manipulated attributes in terms of relative importance are not constant across all experimental cells. For instance, the country of origin ranks first or second in terms of relative importance when defined on four levels (treatments 4, 12, 20, and 26), whereas third or fourth when defined on two levels only. Similarly, memory ranks third or fourth in most experimental cells when defined on two levels, whereas first or second when defined on four levels in treatments 32 and 24 respectively.

Figure 2 represents graphically the estimated relative importance weights of the four manipulated attributes across treatments The estimated relative importance weight of any manipulated attribute is consistently higher when defined on 4 levels than when it is defined on two levels only. Also, for memory (i.e., a relatively unimportant attribute), the difference in estimated relative importance between the 2 and the 4 levels conditions seems greater when conjoint profiles are defined on 5 attributes, than 9 attributes.

Using the estimated relative importance weights for each of the four manipulated attributes as the dependent variable, analysis of variance (ANOVA) was conducted to test the effects of the number of attributes included in the conjoint design, the number of response categories of the rating scale, and the number of levels on which the attributes are defined.

The F-test results for each ANOVA performed (i.e., one ANOVA for each manipulated attribute) are presented in Table 7. F-test values are reported for the three main effects, the three possible 2-way interactions, and the three-way interaction between the factors.

In order to interpret the different effects more easily, four multiple linear regressions (i.e., one for each manipulated attribute) of the estimated relative importance weight were also conducted on the number of attributes, the number of response categories, the number of levels, and all possible interactions. Following Wittink et al., 1992, the regression equations that were estimated can be written as follows:

$$ERIMP_{ij} = f\,(K_j,\ ATT_i,\ REC_i,\ LEV_{ij},\ ATT_i{*}REC_i,\ ATT_i{*}LEV_{ij},$$
$$REC_i{*}LEV_{ij},\ ATT_i{*}REC_i{*}LEV_{ij})$$

Where:

$ERIMP_{ij}$ is the estimated relative importance of the jth attribute for the ith subject,

K is a constant,

ATT_i is the number of attributes on which conjoint profiles were defined for the ith subject, (9 attributes = 1, 5 attributes = -1);

REC_i is the number of response categories of the rating scale available to the ith subject to express the preferences, (7 response categories = -1, 11 response categories = 1);

LEV_{ij} is the number of levels of the jth attribute for the ith subject, (2 levels = -1, 4 levels = 1).

The parameters for the four regression equations, which were all estimated with 248 relative importance weights are provided in table 8, along with the F-tests results. The fit of the multiple linear model is rather poor for colour [R^2=.03, F(7, 240)=.97, p<.451], and price [R^2=.03, F(7, 240)=.98, p<.445]. However, it is somewhat better for the two relatively unimportant attributes, country [R^2=.17, F(7, 240)=7.24, p<.000], and memory [R^2=.07, F(7, 240)=2.55, p<.147].

The "Number of Levels Effect"

The first hypothesis predicts that the estimated relative importance of an attribute increases as the number of intermediate levels used to define that attribute increases. This is the "Number of Levels Effect". As presented in Table 7, column 3, a significant main effect due to the number of levels for all the four manipulated attributes is found: colour [F(1, 240)=6.45, p<.012], country of origin [F(1, 240)=48.53, p<.000], price [F(1, 240)=4.45, p<.036], and memory [F(1, 240)=10.48, p<.001]. Regression coefficients in Table 8 show that all the related regression coefficients are positive. Thus, the higher the number of levels, the higher the estimated relative importance weights. The regression parameters associated to the number of levels effect are 4.59 (p<.011), 8.91 (p<.000), 3.83 (p<.0.34), and 3.22 (p<.001), for colour, country of origin, price, and memory respectively.

Thus the average number of levels effect across attributes is 5.14. For example, the average estimated relative importance of colour is 22.64 (i.e., 27.23 - 4.59) when colour is defined on two levels, and 31.82 (i.e., 27.23 + 4.59) when defined on four levels. If the effect of the independent variable codings of -1 and 1 are taken into account, the estimated relative importance weight of an attribute increases by 10.28% as the number of levels along which it is defined increases from two to four. Thus, the first hypothesis is supported.

The "Number of Levels Effect" and the nature of the attribute

The second hypothesis states that the number of levels effect exists for discrete as well as quasi continuous attributes. Since the number of levels effect is statistically significant across all four ANOVA's reported in Table 7, this hypothesis is also supported

Thus, the number of levels effect is a general effect. It exists not only for quasi continuous attributes (i.e., price and memory), but extends also to essentially discrete attributes (i.e., colour and country of origin).

The "Number of Levels Effect" and the rating scale

The third hypothesis predicts that the number of levels effect is less pronounced for rating scales that have a larger number of response categories. However, ANOVA results in column 2 of Table 7 indicate that the main effect due to the number of response categories is not significant for any of the four manipulated attributes: colour [$F(1, 240)=.00$, $p<.954$], country of origin [$F(1, 240)=.05$, $p<.824$], price [$F(1, 240)=1.50$, $p<.221$], and memory [$F(1, 240)=.35$, $p<.553$]. Also, the interaction effect presented in column labeled 2*3 of Table 7 between the number of levels and the number of response categories of the rating scale is not significant for any of these attributes: colour [$F(1, 240)=.03$, $p<.861$], country of origin [F(1, 240)=.98, p<.324], price [F(1, 240)=1.48, p<.225], and memory [F(1, 240)=.00, p<.987].

These results indicate that increasing the number of response categories from 7 to 11, as it was done in this study, does not influence the number of levels effect. The results also indicate that the estimated relative importance weights are not a function of the number of response categories. This can be observed graphically by looking at Figure 2. The patterns of the estimated relative importance weights when attributes are defined on two and four attributes are very consistent across experimental cells involving 7-point rating scales versus 11-point rating scales. Thus, the third hypothesis is not supported.

The "Number of Levels Effect" and the importance of attributes

The fourth hypothesis predicts that the number of levels effect is less pronounced when the number of levels vary along a relatively important attribute than a relatively unimportant attribute. As mentioned earlier, the experiment was designed such that comparisons in terms of relative importance across attributes are possible only across attributes of the same nature Thus, the relationship between the perceived importance of an attribute and the number of levels effect should be investigated in this study for the two discrete attributes and the two quasi continuous attributes distinctively.

Regression coefficients presented in column 3 of Table 8 for the number of levels effect of the four manipulated attributes provide some support to the fourth hypothesis.

The estimated coefficients which indicate the ***absolute magnitude*** of the number of levels effect for the quasi continuous attributes are: 3.83 (p<.035) for price and 3.22 (p<.001) for memory, and for the discrete attributes: 4.59 (p<.011) for colour and 8.91 (p<.000) for country.

For an attribute, the ***relative magnitude*** of the number of levels effect (i.e., the number of levels effect relatively to the importance of the attribute) is given by the ratio of the absolute magnitude of the number of levels effect to the average -fitted- estimated importance for that attribute. The ***relative magnitude*** of the number of levels effect for the discrete attributes is: .363 for country (8.91/24.57) and .169 for colour (4.59/27.23), and for the quasi continuous attributes: .202 for memory (3.22/15.94) and .123 for price (3.83/ 31.25).

As predicted, these results indicate that the number of levels effect is less pronounced when the number of levels vary along a relatively important attribute (i.e., colour or price) than a relatively unimportant attribute (i.e., country or memory) When the number of levels is larger for a relatively unimportant attribute than for the important ones, respondents may be encouraged to pay more attention to the relatively unimportant attribute than they would otherwise. Thus, the fourth hypothesis is supported

The "Number of Levels Effect" and the number of attributes

The fifth hypothesis predicts that the number of levels effect is less pronounced when the number of attributes used to define conjoint profiles is large than when it is small ANOVA results in column 1 of Table 7 indicate that the main effect due to the number of attributes is not significant for colour [F(1, 240)=.02, p<.893], country of origin [F(1, 240)=.74, p<.39], and price [F(1, 240)=.19, p<.664]. Furthermore, for these three attributes, the interaction effect between the number of attributes and the number of levels is not significant: colour [F(1, 240)=.13, p<.723], country of origin [F(1, 240)=.003, p<.872], and price [F(1, 240)=.09, p<.760].

For memory, however, which is a relatively unimportant attribute, both the main effect due to the number of attributes and the interaction effect between the number of attributes and the number of levels are significant: [F(1, 240)=4.46, p<.036], and [F(1, 240)=4.79, p<.030] respectively. Figure 3 represents the average estimated relative importance weights of the four manipulated attributes across treatments with the number of attributes and the number of levels. For memory, the difference in average importance between the 2 and the 4 levels conditions, which represents the number of levels effect, is larger when conjoint profiles are defined on 5 attributes than when they are defined on 9 attributes.

The regression coefficients for memory are -2.10 (p<.036) for the number of attributes effect, and -2.17 (p<.029) for the interaction effect between the number of attributes and the number of levels, in columns 1 and 1*3 respectively of Table 8. For the 5 attributes condition, as the number of levels increases from 2 to 4, the estimated relative importance of memory increases on average from 12.65 (i.e., 15.94 + 2.10 - 3.22 - 2.17) to 23.43 (i.e., 15.94 + 2.10 + 3.22 + 2.17), that is an increase of 10.78%. For the 9 attributes condition however, as the number of levels increases from 2 to 4, the estimated relative importance of memory increases on average from 12.79 (i.e., 15.94 - 2.10 - 3.22 + 2.17) to 14.89 (i.e., 15.94 - 2.10 + 3.22 - 2.17), that is an increase of 2.10%. The lower the number of attributes and the higher the number of levels, then the higher the estimated relative importance of memory. These results indicate that, for this relatively unimportant attribute, the number of levels effect is less pronounced when the number of attributes used to construct conjoint profiles is high.

It was argued that under full-profile conjoint tasks, where stimuli are defined on many attributes, subjects tend to rely more heavily on a limited set of key attributes when expressing their preferences. By definition, a relatively important attribute is somewhat equally likely to be part of that limited set of attributes as the number of attributes varies. Thus, if respondents are sensitive to the variations in number of levels of an important attribute, it is possible that they are somewhat equally sensitive to these variations when conjoint stimuli are defined only along a varying number of attributes. In other terms, for relatively important attributes, it is possible that the number of levels effect is in fact independent of the number of attributes. This may explain why a non significant interaction effect was observed between the number of levels and the number of attributes for the two relatively important attributes (i.e., colour and price).

For the 5 attributes condition, as the number of levels increases from 2 to 4, the estimated relative importance of colour increases on average from 22.49 (i.e., 27.23 - .24 - 4.59 + .09) to 31.69 (i.e., 27.23 - .04 + 4.59 -.09), that is an increase of 9.20%, and the estimated relative importance of price increases from 29.18 (i.e., 31 25 + 79 - 3 83 + .97) to 34.90 (i.e., 31.25 + .79 + 3.83 - .97), that is an increase of 9.00%. For the 9 attributes condition however, as the number of levels increases from 2 to 4, the estimated relative importance of colour increases on average from 22.79 (i.e., 27.23 + .24 - 4.59 - 09) to 31.95 (i.e., 27.23 + .04 + 4.59 +.09), that is an increase of 9.16%, and the estimated relative importance of price increases 25.66 (i.e., 31.25 - .79 - 3.83 - .97) to 35.26 (i e., 31.25 - .79 + 3.83 + .97), that is an increase of 8.60%. These results, that are also presented graphically in Figure 3, indicate that the number of levels effect for colour (i.e., 9 20% and 9.00% in the 5 and 9 attributes conditions) and price (i.e., 9.16% and 8.60% in the 5 and 9 attributes conditions) are somewhat equal across treatments that differ with respect to the number of attributes. These results provide some support to the explanation that was suggested for the lack of significance of the interaction effect between the number of levels and the number of attributes for the two relatively important attributes.

Regarding the non significant interaction effect between the number of levels and the number of attributes for country which was selected as a relatively unimportant discrete attribute, a similar explanation may also apply. The average self-explicated importance of country was 26.09. Though the difference in average self-explicated importance between colour and country was significant, it may be argued that country was not considered as relatively unimportant by respondents, as opposed to memory with a self-explicated importance of 21.77.

Since in this study the relationship between the magnitude of the number of levels effect and the number of attributes used to construct conjoint profiles is evidenced only for one relatively unimportant attribute, the fifh hypothesis is only partially supported. Also, it is argued that for relatively important attributes the number of levels effect is independent of the number of attributes used to construct conjoint profiles.

SECTION 5

DISCUSSION

SUMMARY OF THE MAIN FINDINGS

The number of levels effect in full-profile conjoint analysis was examined in this study. Specifically, it was attempted to provide additional empirical evidence to the observed effect, and gain insight into the possible relationships between the number of levels effect and the number of attributes included in the conjoint design, the number of response categories of the rating scale respondents use to express their preferences, and the relative importance of the attributes.

The first hypothesis that in full-profile conjoint analysis the estimated relative importance of an attribute increases as the number of intermediate levels used to define that attribute increases was supported. A significant main effect due to the number of levels for the four attributes manipulated in the study was observed.

Also, as predicted by the second hypothesis, the number of levels effect occurred for both discrete (i.e., colour and country of origin) and quasi continuous attributes (price and memory). Thus the number of levels effect is not only a general effect in the sense that it occurs with various conjoint data collection methods, estimation procedures, and types of stimuli, but also because it extends to essentially discrete attributes.

The third hypothesis which predicted that the number of levels effect will be less pronounced with rating scales that have a higher number of response categories was not supported. This result is even more significant. Current explanations for the number of levels effect in full-profile rating conjoint analysis revolve around the notion that rating scale values may not have interval properties but rather have ordinal properties. Therefore, the mathematical explanation provided for ranking tasks may also apply to conjoint analysis of full-profile preference ratings (Wittink et al., 1992). Given this explanation, Wittink (1990) suggests that increasing the number of response alternatives of the rating scale may limit the observed number of levels effect. This study however, does not provide support to this possible explanation. For the four attributes manipulated in the study, the interaction effect between the number of levels and the number of response categories of the rating scale was not significant.

The fourth hypothesis predicted that the number of levels effect is less pronounced when the number of levels vary along a relatively important attribute than a relatively unimportant attribute. This hypothesis was also supported.

Finally, the fifth hypothesis of the study was only partially supported The relationship between the number of attributes of the conjoint design and the number of levels effect was found to be significant for only one relatively unimportant attribute included in the study. For that attribute, it was found that the number of levels effect is less pronounced when the number of attributes of the conjoint profiles is high. However, this was not verified for the three other manipulated attributes. This result is interesting in the sense that it provides some insight into the conditions in which the number of levels effect occurs.

Huber et al. (1993) suggest that under repetitive stimuli rating tasks, where stimuli are defined on many attributes, subjects tend to rely more heavily on a limited set of key attributes to express their preferences. A relatively unimportant attribute is increasingly likely to be part of a limited set of "determinant" attributes on which a subject relies to express his/her preferences as the number of attributes decreases. Thus, the fact that for a relatively unimportant attribute the number of levels effect is significantly greater when the number of attributes is low provides some support to Huber et al.'s suggestion. Similarly, a relatively important attribute (i.e., colour or price) is by definition equally likely to be part the limited set of "determinant" attributes as the number of attributes varies. Thus it is not surprising if the interaction between the number of levels and the number of attributes is not significant for these attributes. To summarize, for a relatively unimportant attribute the number of levels effect is less pronounced when the number of attributes used to define conjoint profiles is high than when it is low.

LIMITATIONS AND FUTURE RESEARCH

In the study, subjects expressed their preferences for conjoint profiles on either a 7-point or an 11-point rating scale. It was found that the interaction between the number of response categories of the rating scale and the number of levels along which the attributes were defined was not significant. Thus, the use of an 11-point rating scale did not limit the observed number of levels effect, as suggested by some researchers (Wittink, 1990).

It is possible however, that the use of a rating scale with a much larger number of response categories (e.g., 100-point rating scale) would lead to some improvements in comparability between attributes defined along unequal number of levels. The scale used in the study was a probability of purchase scale. It is also possible to imagine that other types of rating scales (e.g., profiles' liking) would minimize the number of levels effect. Finally, as suggested by Wittink et al. (1992), other scaling procedures such as magnitude scaling (Lodge, 1981) may also be a solution to limit to the number of levels effect. The effect of other scaling procedures, and rating scales with a larger number of response categories are possible avenues for future research on the number of levels effect. Those research directions are especially valuable since they could lead to rather simple solutions to minimize the number of levels effect for researchers who increasingly rely on full-profile conjoint analysis (Wittink and Cattin, 1989).

The fact that only one attribute (i.e., memory) was distinctly considered as relatively unimportant is the second limitation of the study. Ideally, the hypothesis regarding the interaction between the number of levels and the number of attributes used in the conjoint design should have been supported for at least two unimportant attributes. There are however some indications that country of origin, for which the interaction effect was not significant, was not considered as relatively unimportant as indicated by the self-reported scores in the conjoint study. Further studies on the number of levels effect may concentrate on the issue whether the number of levels effect is indeed more pronounced for a relatively unimportant attribute when conjoint profiles are defined on a small number of attributes (i.e., 5 or less attributes).

The third major limitation of the study lies in the use of a sample of students as respondents. One may be quite confident that the respondents were familiar with the product category that was selected. Also, there is evidence that the validity of conjoint results depends on the educational level of the respondents (Tashian, Roobina, and Slama, 1982). Thus it is possible that the magnitude of the number of levels effect would be higher than what was observed when applied in real conjoint analysis situations. Further studies on the number of levels effect may be conducted where possible with consumers instead of students.

IMPLICATIONS FOR RESEARCHERS

When researchers analyze conjoint results they should be aware that estimated importance weights are not comparable across attributes, when attributes are defined on an unequal number of levels. As suggested by several studies, including this one, the estimated relative importance weight of an attribute increases as the number of levels along which that attribute is defined increases. This applies no matter the nature of the attribute (i.e., discrete or quasi continuous) as indicated by this study, but also to various conjoint data collection methods, estimation procedures, and types of stimuli.

The first recommendation to minimize the number of levels effect is to define when possible all the attributes used to construct conjoint profiles on an equal number of levels (Wittink, 1990). However, such a recommendation may not be always appropriate depending on the objective of the conjoint study. For instance, if conjoint analysis is conducted to elaborate a pricing strategy, the researcher may need to gain insight into the tradeoffs consumers make between several (i.e., more than 4) levels of price and some attributes that are dichotomous in nature (e.g., whether the product possesses a given attribute).

This study showed that unimportant attributes are likely to be subject to the number of levels effect, especially when conjoint profiles are defined along a low number of attributes (i.e., 5 or less attributes). Thus, in situations where conjoint profiles are constructed with only a few attributes, it is likely that the importance weight of unimportant attributes is inflated if those attributes are defined along a relatively high number of levels. Therefore, it is recommended to define unimportant attributes on a number of levels which is at the most equal to the number of levels used to define relatively important attributes. This holds especially if the conjoint design involves five or less attributes. This recommendation somewhat complements previous recommendation by Wittink et al. (1989) that the number of levels to be used for an attribute should be a positive function of the importance of the attribute to the respondent.

The third recommendation relates to the operationalization of the importance of an attribute in conjoint analysis, or more specifically to the use of unacceptable levels. The definition of the relative importance of an attribute (i.e., the ratio of the difference between the largest and smallest part-worth for an attribute to the sum of the differences between the largest and smallest part-worth for all the attributes), which is commonly accepted in conjoint analysis, implies that totally unacceptable levels of an attribute could also be used to estimate the relative importance weights of the attributes. A totally unacceptable level of an attribute is defined here as a level for which any conjoint profile that includes that level is rejected no matter how attractive the other levels of the profile (Srinivasan, 1988).

There are at least three problems with unacceptable levels in conjoint analysis. First, if one includes an unacceptable level of an attribute in the conjoint design, it may inflates undesirably the estimated relative importance weight of that attribute, as commonly computed. It may also impact on the magnitude of the number of levels effect which was shown to be related to the importance of attributes in this study. In addition, it was shown that respondents rarely assign a zero probability of purchase to conjoint profiles that contain unacceptable levels (Mehta, Moore, and Pavia, 1992). Also, there is evidence that in full-profile conjoint analysis some subjects express a high probability of purchase for profiles containing unacceptable levels (Klein, 1986; Green, Krieger, and Agarwal, 1991). Thus, the importance of an attribute should rather be defined as the difference between part-worths of the most desirable level and least desirable *but acceptable* level of that attribute (Srinivasan, 1988).

Therefore, the third recommendation is that when the conjoint analyst defines levels of the attributes, unacceptable levels should be discarded from the conjoint design as much as possible. Unacceptable levels could be identified prior the construction of conjoint profiles through a pretest of the desirability of all levels of each attribute similar to what was done in this study. In general, it is recommended that researchers collect desirability values for all levels of each attribute in addition to full-profile preference ratings. If the construction of conjoint profiles for which the researcher collects preferences reflects a full-factorial design, it is recommended, at the estimation stage, to discard preference ratings for profiles that include unacceptable levels.

CONCLUSION

The number of levels effect is a real problem for conjoint analysts who would like to rely on estimated part-worths to determine attribute importance, which is a particularly relevant approach to understand product or service choices in consumer research. The fact that the number of levels effect occurs across various conjoint data collection methods, estimation procedures, and types of stimuli raises concerns from researchers. In fact, one of the main problem is that popular conjoint analysis methods such as profiles rank order and profiles rating do not minimize the number of levels effect. Since an explanation was developed by researchers for the number of levels effect in conjoint ranking tasks, this study focused mainly on metric conjoint analysis of full-profile ratings.

In this study, further evidence for the number of levels effect in full-profile conjoint analysis was provided, and it was also proved that it extends to attributes that are discrete in nature. Also, the magnitude of the number of levels effect for an attribute was found to decrease with the importance of that attribute. Finally, for unimportant attributes the magnitude of the number of levels effect was found to be a positive function of the number of attributes with which conjoint profiles are constructed.

Unfortunately the hypothesis that the number of levels effect could be minimized by using a rating scale with a higher number of response categories was not supported. However, in that study two types of scales only (i.e., 7-point versus 11-point rating scales) were used. It is possible that scales with a higher number of response categories, or even other scaling procedures could minimize the number of levels effect.

The empirical investigation of the effect of the rating scale on the estimated relative importance weights of the attributes is a major avenue for future research on the number of levels effect in full-profile conjoint analysis. In effect, additional research in that direction may lead to convenient and simple recommendations, that would enable researchers to interpret the importance of attributes without being concerned with the lack of comparability of attributes defined along unequal numbers of levels.

Based on these results as well as previous findings it is recommended, when possible, that researchers define attributes along an equal number of levels. However, such a recommendation may not be always compatible with the objectives of the conjoint study. In general, it is recommended that researchers define unimportant attributes on a number of levels which is at the most equal to the number of levels used to define relatively important attributes, especially if the conjoint design involves five or less attributes. This recommendation somewhat complements previous recommendations that the number of levels to be used for an attribute should be a positive function of that attribute's importance. This presupposes that researchers collect self-explicated importances for attributes they plan to include in their design prior to any conjoint study Finally, it is recommended that the relative importance of an attribute should be computed based on acceptable levels only. In general, in addition to full-profile preferences, researchers should collect desirability values for all levels of each attribute. This would allow researchers to avoid as much as possible to define attributes along unacceptable levels, or to estimate part-worths based on full-profiles that would also include unacceptable levels.

TABLES

AND

FIGURES

Authors	Conjoint Method	Stimuli	Estimation Method	Type of research
Currim, Weinberg, and Wittink (1981)	Paired comparisons	Subscription programs (6 attributes, no manipulation)	OLS	Survey
Wittink, Krishnamurthi, and Nutter (1982)	Full-profile rating Tradeoff paired comparisons	Summer jobs (4 attributes, 2 manipulated)	LINMAP	Experiment
Creyer and Ross (1988)	Full-profile rating	Cars (7 attributes, 1 manipulated)	OLS	Experiment
Mishra, Umesh, and Stern (1989)		5 and 8 attributes	LINMAP MONANOVA OLS	Monte Carlo Simulation
Wittink, Krishnamurthi, and Reibstein (1989)	Tradeoff paired comparisons Full-profile rating Paired profile comparisons	Colour TV, Banking service, Typewriter, Yogourt, Long distance service	OLS	Experiment
Wittink et al. (1992)	ACA Full-profile rating	Refregirator (5/9 attributes, 4 manipulated)	ACA OLS	Experiment

Table 1
Previous Studies on the "Number of Levels Effect"

Corded Residential Telephone Attributes	**μ** Mean	**(σ)** Standard Deviation
The price of the telephone	**5.86**	**(1.26)**
Whether the telephone has a ringer volume control button	**5.74**	**(1.21)**
The telephone's design (keys in the handset versus keys on the base)	**5.40**	**(1.36)**
The telephone's warranty (1 year, 2 years, etc.)	**5.38**	**(1.40)**
The colour of the telephone	**5.31**	**(1.30)**
The length of the handset cord	**5.23**	**(1.23)**
The telephone's possible use (table versus wall telephone)	**5.14**	**(1.51)**
Whether the telephone has a link button (to enable "Call Waiting Service")	**5.06**	**(1.64)**
Whether the telephone has emergency buttons	**4.91**	**(1.55)**
Whether the telephone has a one-touch redial button (to allow automatic redial)	**4.83**	**(1.55)**
The memory of the telephone for frequently dialed numbers	**4.86**	**(1.48)**
The brand name of the telephone (AT&T, GE, Northern Telecom, Panasonic, etc.)	**4.85**	**(1.59)**
Whether the telephone has an incoming call digital display	**4.78**	**(1.69)**
Whether the telephone has a mute button	**4.66**	**(1.65)**
The telephone's dial button's size (small to verly large size)	**4.63**	**(1.22)**
Whether the telephone has an incoming voice volume control button	**4.31**	**(1.60)**
Whether the telephone has a light on keypad (to illuminate at night)	**4.07**	**(1.60)**
Whether the telephone allows handfree dialing	**4.05**	**(1.48)**
Whether the telephone has an ongoing number digital display	**3.97**	**(1.57)**
Whether the telephone has a light to signal incoming call	**3.92**	**(1.83)**
The country of origin of the telephone	**3.35**	**(1.79)**
Whether the telephone has a phone number index card in its base	**3.25**	**(1.56)**

Table 2
Average Self-Reported Importances and Standard Deviations for the 22 Telephone Attributes Initially Selected

Telephone attributes	Attribute levels	μ Mean	(σ) Standard Deviation
Colour:	Black	7.61	(2.30)
	White	6.86	(2.32)
	Ivory	6.42	(2.98)
	Grey	5.53	(2.23)
	Blue	4.55	(2.32)
	Light blue	3.61	(2.18)
	Red	3.58	(2.52)
	Light red	3.11	(2.06)
Brand name:	Northern Telecom	7.56	(1.73)
	AT&T	7.18	(1.86)
	Panasonic	6.92	(1.93)
	General Electric	5.56	(2.17)
	Telemax	4.54	(2.11)
	Conair	3.59	(1.80)
Dial button's size:	Regular size	8.28	(1.54)
	Large size	5.60	(2.37)
	Small size	3.73	(2.83)
	Very large size	3.08	(2.42)
Country of origin:	Canada	7.73	(1.34)
	Japan	7.47	(1.69)
	USA	7.04	(1.88)
	Taiwan	[illegible]	(1.56)
	Thailand	4.35	(1.57)

Table 3
Average Self-Reported Preferences and Standard Deviations
for Selected Levels of Brand, Colour, Dial Button's Size, and Country of Origin

Attribute	Levels
Telephone's colour:	Black (*), Ivory, Blue, Red (*)
The country of origin of the telephone:	Canada (*), Japan, USA, Taiwan (*)
The price of the telephone:	$40 (*), $55, $70, $85 (*)
The number of memorized numbers (i.e., memory):	5 (*), 10, 15, 20 (*)
Whether the telephone has a ringer volume control button:	Yes, No
The length of the telephone's warranty:	1 year, 2 years
Whether the telephone has a one-touch redial button:	Yes, No
Whether the telephone has emergency buttons:	Yes, No
The design of the telephone:	Keys on the base, Keys in the handset

Table 4
Corded Residential Telephone Attributes and Their Associated Levels

(*) indicates "extreme levels" which were used to define manipulated attributes on 2 levels.

Note: The five first attributes (i.e., the four manipulated attributes and the ringer volume control button attribute) were the five attributes selected in those experimental cells where conjoint profiles were constructed with 5 attributes. In experimental cells where conjoint profiules were constructed with 9 attributes all these attributes were included in the conjoint design.

Attribute	9 attributes										5 attributes										Mean and standard deviation across cells:	
	7 response categories					11 response categories					7 response categories					11 response categories					μ Mean	(σ) Standard Deviation
Colour	26.1	31.7	7.9	19.9	20.4	23.3	32.7	20.3	22.7	27.7	24.4	32.8	15.2	22.6	23.1	26.9	30.2	22.2	14.0	17.0	23.75	(18.52)
# of levels:	2	4	2	2	2	2	4	2	2	2	2	4	2	2	2	2	4	2	2	2		
Rank (*):	*1*	*1*	*4*	*3*	*2*	*2*	*1*	*2*	*2*	*1*	*2*	*1*	*3*	*2*	*3*	*2*	*1*	*2*	*4*	*4*		
Country	15.7	16.1	29.7	23.7	16.7	16.4	17.7	32.1	7.8	13.8	18.3	12.3	34.2	17.0	12.3	14.2	11.8	38.0	12.9	19.2	17.75	(13.91)
# of levels:	2	2	4	2	2	2	2	4	2	2	2	2	4	2	2	2	2	4	2	2		
Rank:	*3*	*3*	*2*	*2*	*3*	*3*	*3*	*1*	*4*	*4*	*3*	*4*	*1*	*3*	*4*	*3*	*4*	*1*	*3*	*3*		
Price	24.9	26.2	35.4	29.9	33.6	31.1	30.7	17.0	36.7	24.0	29.7	18.8	26.0	31.4	27.6	34.1	18.7	14.8	42.3	20.7	28.55	(19.95)
# of levels:	2	2	2	4	2	2	2	2	4	2	2	2	2	4	2	2	2	2	4	2		
Rank:	*2*	*2*	*1*	*1*	*1*	*1*	*2*	*4*	*1*	*2*	*1*	*2*	*2*	*1*	*1*	*1*	*3*	*3*	*1*	*2*		
Memory	12.7	10.8	11.6	13.8	12.5	12.3	5.8	17.4	18.9	17.3	11.8	13.8	10.8	10.9	24.6	12.3	20.5	9.3	14.5	22.3	13.59	(10.99)
# of levels:	2	2	2	2	4	2	2	2	2	4	2	2	2	2	4	2	2	2	2	4		
Rank:	*4*	*4*	*3*	*4*	*4*	*4*	*4*	*3*	*3*	*3*	*4*	*3*	*4*	*4*	*2*	*4*	*2*	*4*	*2*	*1*		
Treatment #:	1	2	4	6	8	9	10	12	14	16	17	18	20	22	24	25	26	28	30	32	**Total sample size:**	
Number of subjects:	35	7	7	9	9	28	8	9	7	8	28	8	7	10	9	28	7	6	10	8	248 (n)	

Table 5
Average Relative Importance Weights and Average Rank Orders in Terms of Importance For the Four Manipulated Attributes Across Experimental Cells

(*) The rank refers to the rank order in mean importance for colour, country, price and memory in a column (i.e., treatment) of this table from the highest (1) to the lowest (4)

Attribute	9 attributes								5 attributes							
	7 response categories				11 response categories				7 response categories				11 response categories			
	Estimated Importance		Self-explicated Importance		Estimated Importance		Self-explicated Importance		Estimated Importance		Self-explicated Importance		Estimated Importance		Self-explicated Importance	
Colour	26.1	31.7	27.2	15.1	23.3	32.7	22.4	23.3	24.4	32.8	26.7	20.0	26.9	30.2	25.4	14.0
# of levels:	2	4	2	4	2	4	2	4	2	4	2	4	2	4	2	4
Treatment #:	1	2	1	2	9	10	9	10	17	18	17	18	25	26	25	26
Country	15.7	29.7	20.8	9.3	16.4	32.1	19.6	17.9	18.3	34.2	23.9	25.7	14.2	38.0	16.3	33.0
# of levels:	2	4	2	4	2	4	2	4	2	4	2	4	2	4	2	4
Treatment #:	1	4	1	4	9	12	9	12	17	20	17	20	25	28	25	28
Price	24.9	29.9	38.0	34.4	31.1	36.7	44.2	46.4	29.7	31.4	34.4	58.7	34.1	42.3	40.6	28.0
# of levels:	2	4	2	4	2	4	2	4	2	4	2	4	2	4	2	4
Treatment #:	1	6	1	6	9	14	9	14	17	22	17	22	25	30	25	30
Memory	12.7	12.5	14.0	10.0	12.3	17.3	13.7	11.1	11.8	24.6	15.4	17.2	12.3	22.3	17.8	21.5
# of levels:	2	4	2	4	2	4	2	4	2	4	2	4	2	4	2	4
Treatment #:	1	8	1	8	9	16	9	16	17	24	17	24	25	32	25	32

Table 6

Average Relative Importance Weights and Average Self-Explicated Importances
the Four Manipulated Attributes Within Selected Experimental Cells

<u>Attribute</u>	Number of attributes	Number of response categories	Number of levels					Mean Estimated Importance Across Cells
	1	2	3	1 * 2	1 * 3	2 * 3	1 * 2 * 3	μ
Colour	0.02	0.00	6.45**	0.13	0.00	0.03	0.02	23.75
	(.893)	*(.95[illegible])*	*(.012)*	*(.723)*	*(.957)*	*(.861)*	*(.884)*	
Country	0.74	0.05	48.53**	0.03	1.33	0.98	0.01	17.75
	(.390)	*(.824)*	*(.000)*	*(.872)*	*(.250)*	*(.324)*	*(.907)*	
Price	0.19	1.50	4.45*	0.09	0.29	1.48	0.07	28.55
	(.664)	*(.221)*	*(.036)*	*(.760)*	*(.594)*	*(.225)*	*(.785)*	
Memory	4.46*	0.35	10.48**	0.57	4.79*	0.00	1.11	13.59
	(.036)	*(.553)*	*(.001)*	*(.452)*	*(.030)*	*(.987)*	*(.293)*	

Table 7

F-Test results for the Analysis of Variance (ANOVA)

** P < 01
* P < 05

Attribute	Constant	Number of attributes	Number of response categories	Number of levels					R2	F
	Ct.	1	2	3	1 * 2	1 * 3	2 * 3	1 * 2 * 3		
Colour	27.23**	0.24	-0.11	4.59*	0 64	0.09	-0 31	0 26	0.03	0.97
Country	24.57**	-1.10	0.28	8.91**	-0 20	-1.47	1.26	-0.15	0.17	7.24**
Price	31.25**	-0.79	2.22	3.83*	-0.56	-0.97	2.21	-0.49	0.03	0.98
Memory	15.94**	-2.10 *	0.59	3.22**	0.74	-2.17 *	0 02	1.05	0.06	2.55*

Table 8

Multiple Regression Coefficients for Equations Predicting Estimated Relative Importance Weights

** P < .01
* P < .05

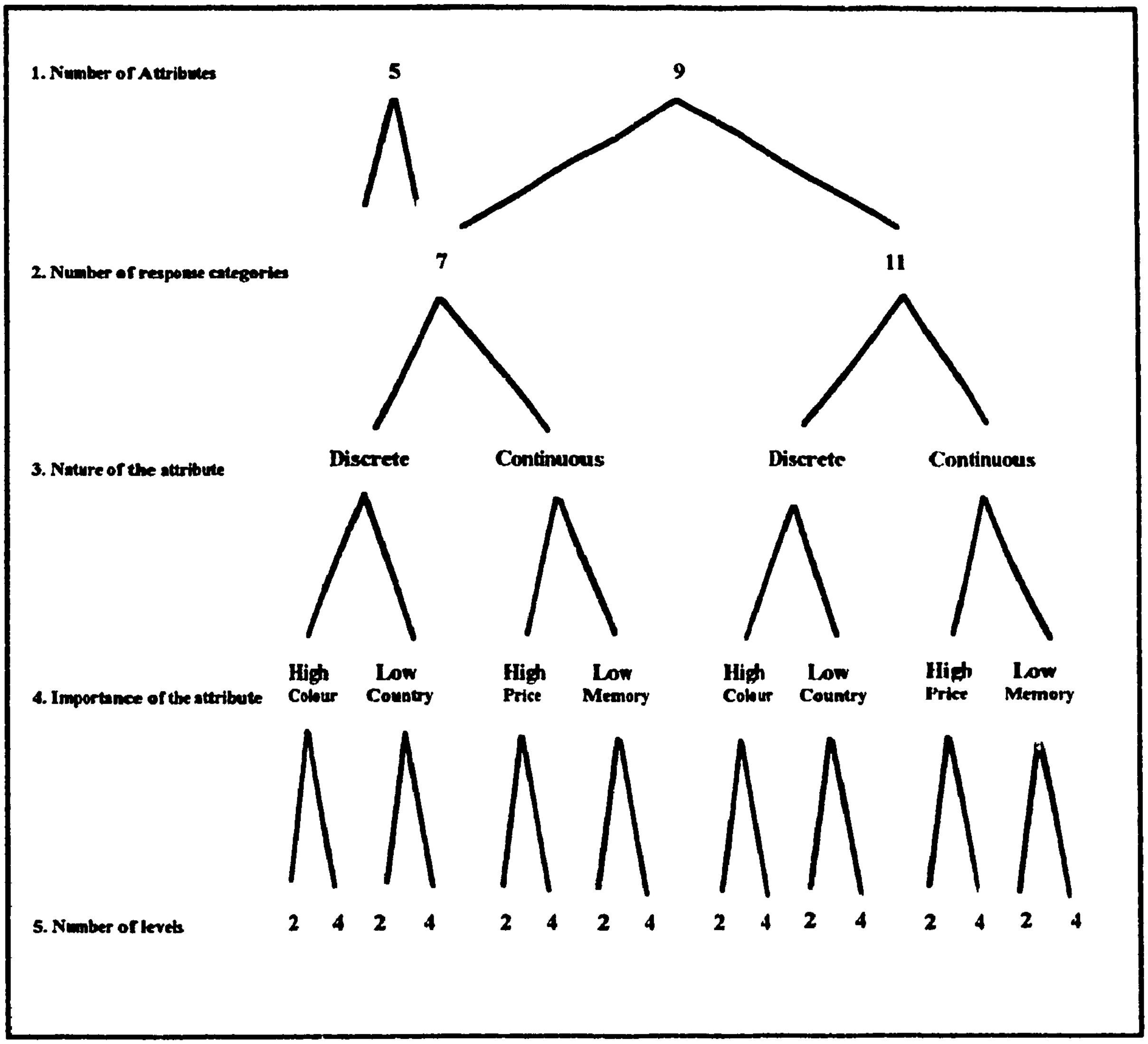

Figure 1
Experimental Design

Note The attributes which were manipulated were color (2 or 4 levels), country of origin (2 or 4 levels), number of memorized numbers (2 or 4 levels), and price (2 or 4 levels) Please refer to Table 4 for a complete list of the attributes and their levels

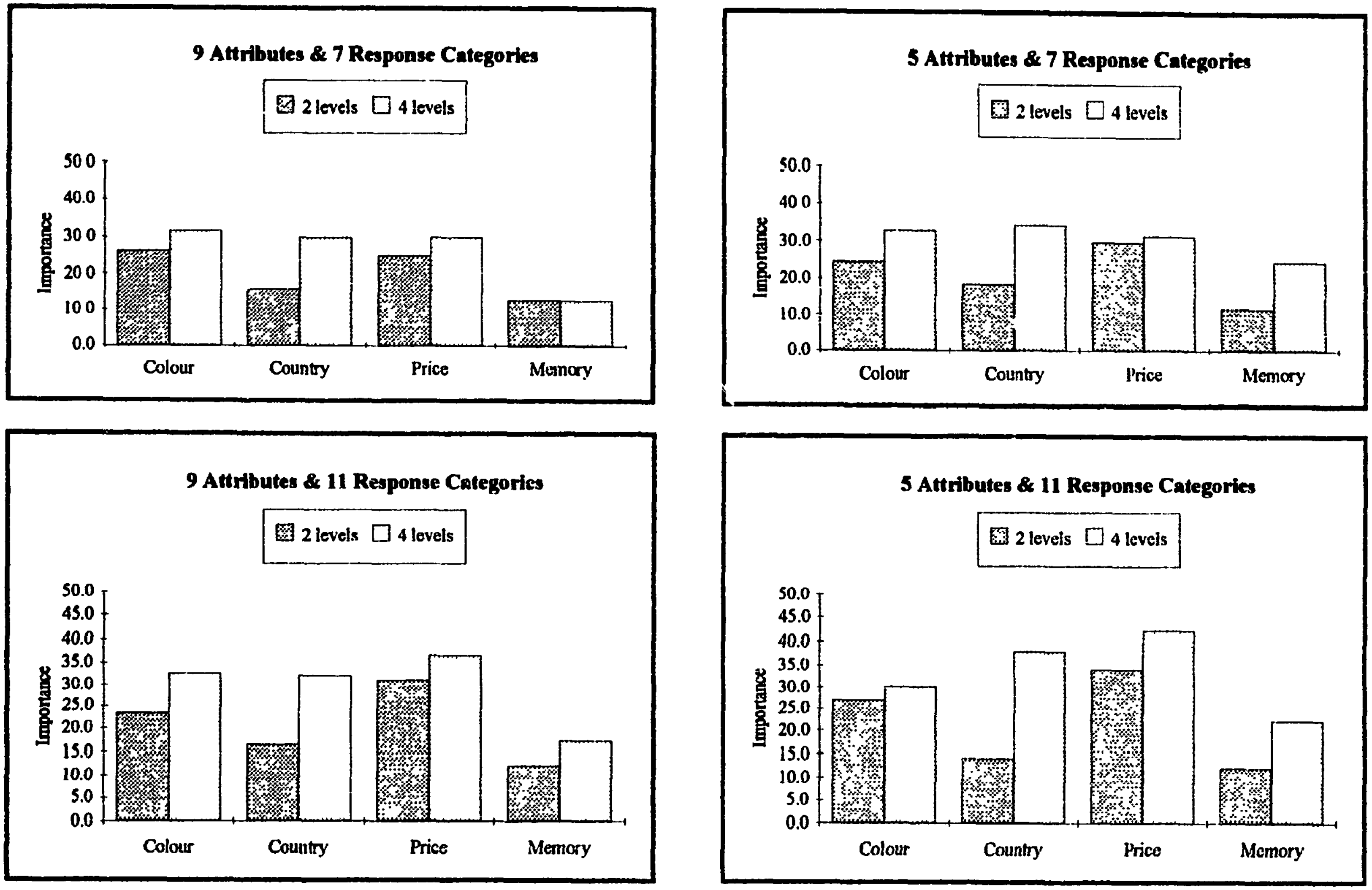

Figure 2

Average Estimated Relative Importance Weigths for the Four Manipulated Attributes with Number of Attributes, Number of Response Categories, and Number of Levels

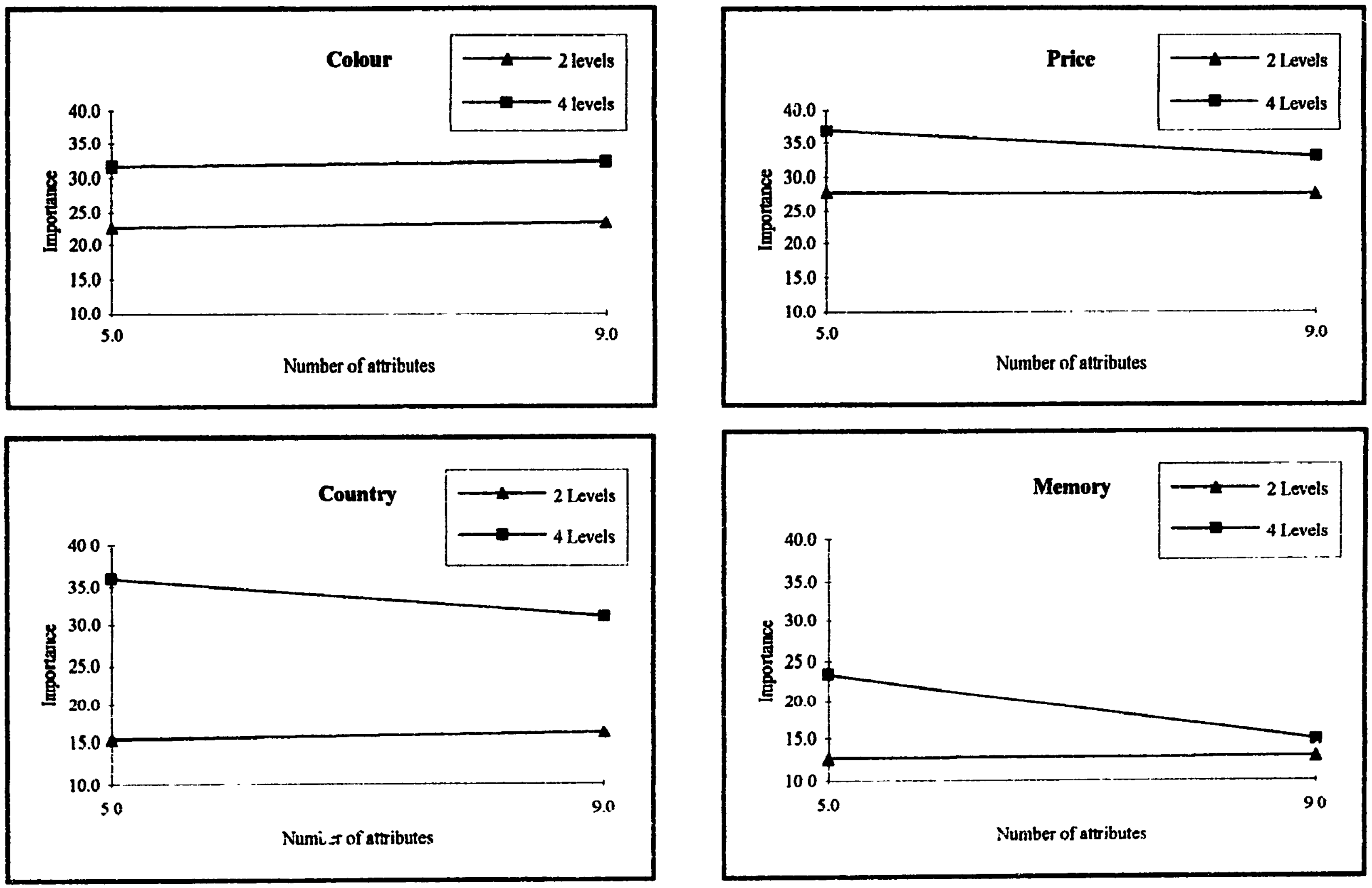

Figure 3

Average Estimated Relative Importance Weigths for the Four Manipulated Attributes

with Number of Attributes and Number of Levels

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APPENDIX 1

A MATHEMATICAL EXPLANATION FOR THE NUMBER OF LEVELS EFFECT FOR ORDINARY LEAST SQUARES ESTIMATION OF RANK-ORDER PREFERENCES

Example: Simulation

Following the example provided by Wittink (1990), some insight into the number of levels effect in the case rank-order preferences are collected and OLS is used to estimate part-worths may be gained by conducting a quick simulation.

It is assumed that rank-order preferences are collected for a set of stimuli (e.g. products) that are defined on two attributes. The first attribute is whether the stimulus possesses a certain feature (yes, no), and the second attribute is the price. The feature is essentially dichotomous and is defined on two levels. The price is defined in the simulation on two, three, and five levels. It is assumed that the feature makes the product more attractive, and that lower prices are preferred over higher prices.

Then, it is assumed that rank order preferences are collected from two subjects (i.e., A and B), who show respectively a minimum and a maximum price sensitivity. Thus for instance, in the 2 x 2 design, the rank-order preferences for A and B is as follows:

Stimulus	Rank-order subject A	Rank-order subject B
Feature, $10	1	1
Feature, $14	2	3
No feature, $10	3	2
No feature, $14	4	4

In all designs (i.e., 2x2, 2x3, and 2x5 cases), the part-worths are estimated by ordinary least square. For each subject and across designs, a relative importance weight for the two attributes is computed. The relative importance weight of an attribute is defined as the ratio of difference between the largest and smallest part-worth for that attribute to the sum of the differences between the largest and smallest part-worth for the two attributes.

The following table shows the systematic effect of the number of levels on the estimated relative importance of the attribute.

Stimulus		Subject A (Minimum price sensitivity) Part-Worth	Estimated Importance	Subject B (Maximum price sensitivity) Part-Worth	Estimated Importance
Feature:	Yes	+1.0		+0.5	
	No	-1.0	(0.67)	-0.5	(0.33)
Price:	$12	+0.5		+1.0	
	$14	-0.5	**(0.33)**	-1.0	**(0.67)**
Feature:	Yes	+1.5		+0.5	
	No	-1.5	(0.60)	-0.5	(0.20)
Price:	$10	+1.0		-2.0	
	$12	0		0	
	$14	-1.0	**(0.40)**	+2.0	**(0.80)**
Feature:	Yes	+2.5		+0.5	
	No	-2.5	(0.56)	-0.5	(0.11)
Price:	$10	+2.0		+4.0	
	$11	+1.0		+2.0	
	$12	0		0	
	$13	-1.0		-2.0	
	$14	-2.0	**(0.44)**	-4.0	**(0.89)**

As the number of levels of price increases, both the maximum (i e., subject B) and the minimum (i.e., subject A) relative importance of the price increases. In other terms, in ordinary least squares estimation of rank-order preferences, both the maximum and the minimum importance weight an attribute can achieve are constrained, as soon as a number of levels to define that attribute is selected.

As indicated by a comprehensive simulation study conducted by Wittink, Krishnamurthi, and Reibstein (1989), the number of levels effect exists no matter the number of attributes involved in the conjoint design. Also, increasing the number of input values (i.e., subjects' preferences) does correct the number of levels effect.

Mathematical formulas

Wittink, Huber, Fiedler, and Miller (1992) further showed that in ordinary least squares estimation of rank-order preferences (assuming a lexicographic processing of the stimuli is observed by the respondents), the maximum importance of an attribute j is constrained to be:

$$\max I_j = (l_j - 1) \prod l_k \quad (k \neq j)$$

Where:

k is the number of attributes (1, 2, ... , k),

l_k is the number of levels for the kth attribute,

I_j is the importance of the jth attribute.

Also, the minimum importance of an attribute j is constrained to be:

$$\min I_j = (l_j - 1).$$

APPENDIX 2

SURVEY INSTRUMENT FOR THE PRETEST

CONSUMER SURVEY OF CORDED RESIDENTIAL TELEPHONES

Thank you for your participation in this survey that has no commercial purposes. This study is conducted by a graduate student in the M.Sc. in Administration Programme at Concordia University for an M.Sc.A. thesis. The objective of this study is to obtain students' opinions regarding ***residential corded telephones.*** *In particular, we are interested in those factors that are important to you when acquiring a new corded residential telephone. Please be assured that your answers to this survey will be kept strictly confidential.*

Please complete this questionnaire sometime during this week, and bring the completed questionnaire to this class next week. There will be a lottery, and two students who complete the questionnaire will receive a prize of $ 20 each. If you would like to participate in the lottery, please print your name on the first page attached to the questionnaire. This page will be removed when you hand in your questionnaire.

1. IMPORTANCE OF SOME FACTORS WHEN PURCHASING A NEW RESIDENTIAL TELEPHONE

Please evaluate the following factors that may be considered when purchasing a new corded residential telephone. Read each factor carefully and rate how important that factor would be to you as if you were purchasing a new corded residential telephone. Please rate each factor on the following scale of 1 to 7, with 1 being very unimportant and 7 being very important. For each factor, please circle the number on the right that best reflects your opinion about its importance.

How important to you is ...	Very Unimportant	Unimportant	Somewhat Unimportant	Undecided	Somewhat Important	Important	Very Important
The telephone's possible use (Table telephone, wall telephone, table or wall convertible telephone)	1	2	3	4	5	6	7
The length of the handset cord	1	2	3	4	5	6	7
The price of the telephone	1	2	3	4	5	6	7
The telephone's warranty (None, 1 year, 2 years, etc.)	1	2	3	4	5	6	7
The brand name of the telephone (AT&T, Conair, GE, Northern Telecom, Panasonic, Telemax)	1	2	3	4	5	6	7
Whether the telephone has one-touch redial button	1	2	3	4	5	6	7

How important to you is ...	Very Unimportant	Unimportant	Somewhat Unimportant	Undecided	Somewhat Important	Important	Very Important
Whether the telephone has a mute or hold button (To provide privacy by preventing the caller from momentarily hearing your conversations with others in the room)	1	2	3	4	5	6	7
Whether the telephone has emergency buttons (To dial automatically emergency numbers)	1	2	3	4	5	6	7
The colour of the telephone	1	2	3	4	5	6	7
The telephone's design (please refer to page 4) (Keys in the handset telephone versus keys on the telephone's base)	1	2	3	4	5	6	7
The country where the telephone was manufactured	1	2	3	4	5	6	7
The size of the dial buttons (please refer to page 4) (Small size to very large size dial buttons)	1	2	3	4	5	6	7
Whether the telephone has an incoming voice volume control (To adjust the volume of the caller's voice)	1	2	3	4	5	6	7
Whether the telephone has a ringer volume control (Ringer off, low, medium, high)	1	2	3	4	5	6	7
Whether the telephone has a link button (To enable Call Waiting service and other related services)	1	2	3	4	5	6	7
Whether the telephone allows handfree dialing (To dial telephone numbers without having to hold the handset)	1	2	3	4	5	6	7
Whether the telephone has memory for frequently dialed numbers	1	2	3	4	5	6	7
Whether the telephone nas a light on the keypad to illuminate at night	1	2	3	4	5	6	7
Whether the telephone has a light to signal incoming calls	1	2	3	4	5	6	7
Whether the telephone has a phone number index card in its base	1	2	3	4	5	6	7
Whether the telephone has an ongoing number digital display (To check that numbers are correctly dialed)	1	2	3	4	5	6	7
Whether the telephone has an incoming call digital display (To identify and screen callers)	1	2	3	4	5	6	7

2. PREFERENCES FOR CERTAIN PRODUCT ATTRIBUTES WHEN PURCHASING A NEW RESIDENTIAL TELEPHONE

Please, go over the telephone brands that are mentioned below. Assume that these different brand names correspond to different telephones that are similar in terms of all other attributes except for the brand name. Which brand would be the most desirable to you ? Please circle 9 for this brand. Then, rate **all** the remaining brands in relation to the most desirable brand by circling a number from 1 to 9 expressing the desirability of the remaining brands. You may circle the same number for two equally desirable brands.

The brand name of the telephone:									Most desirable Brand
AT&T	1	2	3	4	5	6	7	8	9
CONAIR	1	2	3	4	5	6	7	8	9
GENERAL ELECTRIC	1	2	3	4	5	6	7	8	9
NORTHERN TELECOM	1	2	3	4	5	6	7	8	9
PANASONIC	1	2	3	4	5	6	7	8	9
TELEMAX	1	2	3	4	5	6	7	8	9

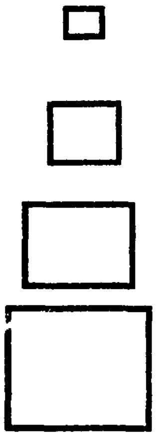
Now, please repeat what you just did for the telephone colors. Go over the telephone colours that are mentioned below. Assume that these different telephone colours correspond to different telephones that are similar in terms of all other attributes except for their colours. Which colour would be the most desirable to you ? Please circle 9 for this colour. Then, rate **all** the remaining colours in relation to the most desirable colour by circling a number from 1 to 9 expressing the desirability of the remaining colours. You may circle the same number for two equally desirable colors

The telephone's colour:									Most desirable Colour
Black	1	2	3	4	5	6	7	8	9
Blue	1	2	3	4	5	6	7	8	9
Grey	1	2	3	4	5	6	7	8	9
Ivory	1	2	3	4	5	6	7	8	9
Light blue	1	2	3	4	5	6	7	8	9
Light red	1	2	3	4	5	6	7	8	9
Red	1	2	3	4	5	6	7	8	9
White	1	2	3	4	5	6	7	8	9

Now, please repeat what you just did for each of the following attributes. Select the most desirable attribute and circle 9 for this attribute. Then, rate **all** the remaining attributes in relation to the most desirable attribute by circling a number from 1 to 9 to express their desirability.

The country where the telephone was manufactured:									Most desirable Country
Canada	1	2	3	4	5	6	7	8	9
Japan	1	2	3	4	5	6	7	8	9
Taiwan	1	2	3	4	5	6	7	8	9
Thailand	1	2	3	4	5	6	7	8	9
USA	1	2	3	4	5	6	7	8	9

The dial buttons' size:

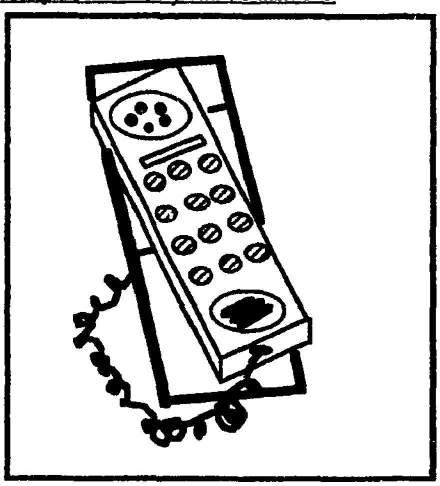


									Most desirable Button's size
Small size (0 6 X 0.6 cm)	1	2	3	4	5	6	7	8	9
Regular size (1.1 X 1.1 cm)	1	2	3	4	5	6	7	8	9
Large size (1.6 X 1.6 cm)	1	2	3	4	5	6	7	8	9
Very large size (2.1 X 2.1 cm)	1	2	3	4	5	6	7	8	9

Different types of telephone design

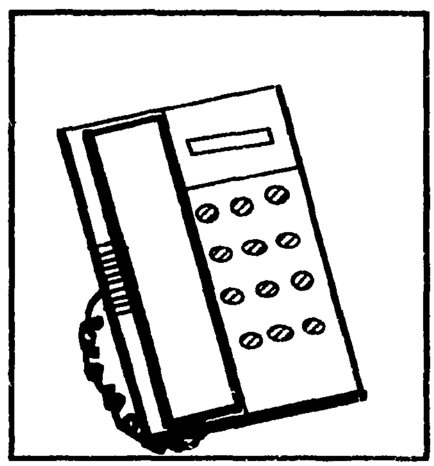
A

Telephone with keys in the handset



B

Telephone with keys on the base



Thank you for your participation.

APPENDIX 3

SURVEY INSTRUMENT FOR THE CONJOINT STUDY

CONSUMER SURVEY OF CORDED RESIDENTIAL TELEPHONES

*Thank you for your participation in this survey that has no commercial purposes. This study is conducted by a graduate student in the M.Sc. in Administration Programme at Concordia University for an M.Sc.A thesis. The objective of this study is to obtain students' opinions regarding **residential corded telephones**. In particular, we are interested in those factors that are important to you when acquiring a new corded residential telephone. Please be assured that your answers to this survey will be kept strictly confidential*

Please complete this questionnaire sometime during this week, and bring the completed questionnaire to this class next week. There will be a lottery, and two students who complete the questionnaire will receive a prize of $ 20 each. If you would like to participate in the lottery, please print your name on the first page attached to the questionnaire. This page will be removed when you hand in your questionnaire.

1. YOUR PREFERENCES FOR DIFFERENT CORDED RESIDENTIAL TELEPHONES

Please imagine you are thinking of purchasing a new corded residential telephone You will examine some descriptions of corded residential telephones, and then state how likely you would be to consider **each** described telephone as a possible corded residential telephone for yourself

For example, read the following description carefully:

The telephone: is black
has a one-touch redial button
has the keys on the base
is made in Taiwan
has no emergency buttons
has a 2 years warranty
has memory for 5 frequently dialed numbers
has a price of $ 40
has a ringer volume control button

How likely would you be to consider the above as a possible corded residential telephone for yourself if you were purchasing a corded residential telephone today? Please go over the following terms from left to right and then circle around one of the numbers that matches your likelihood most closely. Note that the likelihood ranges from 0 to 10, 0 being "no chance" and 10 being "certain"

No Chance	very slight possibility	slight possibility	some possibility	fair possibility	fairly good possibility	good possibility	probable	very probable	almost sure	certain
0	1	2	3	4	5	6	7	8	9	10

Please repeat what you just did for **each** of the following descriptions of corded residential telephones.

The telephone: is red
has a one-touch redial button
has the keys on the base
is made in Taiwan
has emergency buttons
has a 1 year warranty
has memory for 20 frequently dialed numbers
has a price of $ 85
has no ringer volume control button

No Chance	very slight possibility	slight possibility	some possibility	fair possibility	fairly good possibility	good possibility	probable	very probable	almost sure	certain
0	1	2	3	4	5	6	7	8	9	10

The telephone: is blue
has no one-touch redial button
has the keys on the base
is made in Taiwan
has no emergency buttons
has a 2 years warranty
has memory for 5 frequently dialed numbers
has a price of $ 40
has no ringer volume control button

No Chance	very slight possibility	slight possibility	some possibility	fair possibility	fairly good possibility	good possibility	probable	very probable	almost sure	certain
0	1	2	3	4	5	6	7	8	9	10

The telephone: is black
has no one-touch redial button
has the keys on the base
is made in Taiwan
has emergency buttons
has a 2 years warranty
has memory for 20 frequently dialed numbers
has a price of $ 85
has a ringer volume control button

No Chance	very slight possibility	slight possibility	some possibility	fair possibility	fairly good possibility	good possibility	probable	very probable	almost sure	certain
0	1	2	3	4	5	6	7	8	9	10

The telephone: is ivory
has a one-touch redial button
has the keys on the base
is made in Canada
has emergency buttons
has a 1 year warranty
has memory for 5 frequently dialed numbers
has a price of $ 85
has no ringer volume control button

No Chance	very slight possibility	slight possibility	some possibility	fair possibility	fairly good possibility	good possibility	probable	very probable	almost sure	certain
0	1	2	3	4	5	6	7	8	9	10

The telephone: is red
has a one-touch redial button
has the keys in the handset
is made in Canada
has emergency buttons
has a 1 year warranty
has memory for 5 frequently dialed numbers
has a price of $ 85
has a ringer volume control button

No Chance	very slight possibility	slight possibility	some possibility	fair possibility	fairly good possibility	good possibility	probable	very probable	almost sure	certain
0	1	2	3	4	5	6	7	8	9	10

The telephone: is blue
has no one-touch redial button
has the keys on the base
is made in Canada
has emergency buttons
has a 1 year warranty
has memory for 20 frequently dialed numbers
has a price of $ 40
has a ringer volume control button

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0	1	2	3	4	5	6	7	8	9	10

The telephone:

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has a one-touch redial button
has the keys in the handset
is made in Taiwan
has emergency buttons
has a 2 years warranty
has memory for 5 frequently dialed numbers
has a price of $ 85
has a ringer volume control button

No Chance	very slight possibility	slight possibility	some possibility	fair possibility	fairly good possibility	good possibility	probable	very probable	almost sure	certain
0	1	2	3	4	5	6	7	8	9	10

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has a price of $ 40
has a ringer volume control button

No Chance	very slight possibility	slight possibility	some possibility	fair possibility	fairly good possibility	good possibility	probable	very probable	almost sure	certain
0	1	2	3	4	5	6	7	8	9	10

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No Chance	very slight possibility	slight possibility	some possibility	fair possibility	fairly good possibility	good possibility	probable	very probable	almost sure	certain
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No Chance	very slight possibility	slight possibility	some possibility	fair possibility	fairly good possibility	good possibility	probable	very probable	almost sure	[illegible]
0	1	2	3	4	5	6	7	8	9	.0

The telephone:
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0	1	2	3	4	5	6	7	8	9	10

The telephone:
is red
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has the keys in the handset
is made in Canada
has emergency buttons
has a 2 years warranty
has memory for 5 frequently dialed numbers
has a price of $ 40
has no ringer volume control button

No Chance	very slight possibility	slight possibility	some possibility	fair possibility	fairly good possibility	good possibility	probable	very probable	almost sure	certain
0	1	2	3	4	5	6	7	8	9	10

The telephone:
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has a price of $ 85
has no ringer volume control button

No Chance	very slight possibility	slight possibility	some possibility	fair possibility	fairly good possibility	good possibility	probable	very probable	almost sure	certain
0	1	2	3	4	5	6	7	8	9	10

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0	1	2	3	4	5	6	7	8	9	10

The telephone:
- is black
- has a one-touch redial button
- has the keys in the handset
- is made in Canada
- has emergency buttons
- has a 1 year warranty
- has memory for 5 frequently dialed numbers
- has a price of $ 40
- has a ringer volume control button

No Chance	very slight possibility	slight possibility	some possibility	fair possibility	fairly good possibility	good possibility	probable	very probable	almost sure	certain
0	1	2	3	4	5	6	7	8	9	10

2. IMPORTANCE OF CERTAIN PRODUCT ATTRIBUTES WHEN PURCHASING A NEW CORDED RESIDENTIAL TELEPHONE

Please evaluate the changes in the following attributes of corded residential telephones. Read each of the changes carefully.

Changing the color from red to black or ivory . . . . ________

Buying a telephone made in Canada or Japan instead of Taiwan . . . . ________

Increasing the memory for frequently dialed numbers from 5 numbers to 20 . ________

Reducing the price of the telephone from $ 85 to to $ 40 . . . . ________

Total: 100

Now divide 100 points between the above mentioned changes so that the higher the points you assign to a change, the more important it is to you.

Thank you for your participation.