A C T A   U N I V E R S I T A T I S   L O D Z I E N S I S
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BETTER PREDICTION OF PREFERENCES WITH INDIVIDUALIZED SETS OF RELEVANT ATTRIBUTES?

1. Introduction

The philosophy of marketing tells us that the product a company is offering has to satisfy consumers' needs and the better it satisfies them the more succesful the company will be. Following this concept it is extremely necessary for a manufacturer to know what customers want and to understand their choice behavior. In consumer behavior research preference formation as a part of the choice process 17.3 is of special interest. In industrial applications conjoint analysis is the most widely applied technique for estimating consumer's preference function [5]. Introduced to market research in the early 70s [6] the number of commercial applications is estimated to be about 1000 in the USA alone [2].

Given the overall evaluations of a respondent for a set of alternatives, defined in terms of levels of selected attributes, in conjoint analysis one looks for the parameters of a prespecified preference function |7|. One great advantage of the methodology is that analysis is done at the level of the individual respondent, thereby avoiding the problem of the "majority fallacy" [16] common to aggregate level analysis. Figure 1 illustrates some steps in applying the methodology [7].

The focus of this paper is on step 1, the selection of the relevant set of attributes prior to data collection. Although of considerable importance for the quality of a conjoint study this is a frequently overlooked task [15]. In order to explain preference in terms of product attributes it is necessary to find those attributes which determine preference. When the number of poten-

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Select relevant attributes

Select a model of preference

Select data collection method (full-profile or two-factor-at-a-time procedure)

Construct stimuli for the full-profile approach

Select a measurement scale for measuring preference

Present stimuli and measure preferences

Estimate parameters of the preference functions

Fig. 1. Steps in conjoint analysis

tially relevant attributes is large (this is true in many industrial conjoint studies) this task becomes very difficult, because only few attributes can be selected for conjoint analysis for two reasons. First the number of profiles the respondent has to react to increases when more attributes are used [15]. The more important reason is the danger of information overload if preference data are collected by means of a full-profile approach, which is clearly preferred in commercial applications [2]. As emphasized by Green and Srinivasan [7] it is very difficult for respondents to evaluate objects described on more than six attributes.

Below problems associated with the usual way of dealing with this conflict are discussed. Based on these considerations an alternative approach is proposed and the results of an empirical study using this approach are presented.

2. Attribute Selection for Conjoint Analysis - The Usual Way

Typically we find a two-step-procedure:

First a preliminary list of potentially relevant attributes is generated using expert judgments (product manager, sales personnel etc.) and information material on the alternate products in the market. In many cases consumer judgments are used, too. The most popular techniques used for this purpose are group interviews, direct questioning [20], Kelly's repertory grid [12,19] and protocols [22,18].

The more difficult task is to select some attributes out of this preliminary list of potentially relevant attributes for conjoint analysis. To choose those attributes that are "most important for a great part of the respondents" a pre-study has to be conducted. There are different ways to measure attribute importance which lead to different importance weights [10] and as a consequence to different sets of relevant attributes. Self-explicated importance weights [24], the information display board method [23,13] and analysis of protocols [21] are some alternatives to get importance measures.

As an illustration for this two-step-procedure see the conjoint study of J a i n, A c i t o, M a l h o t r a and M a h a j a n [14], who as the first step used Kelly's repertory grid procedure, then asked respondents to rate the identified attributes in terms of their relative importance on a 7-point Likert type of scale and, finally, selected 5 attributes on the basis of the frequency of attribute mentions and the average importance ratings.

Despite this enormous effort in finding relevant attributes this method does by no means guarantee that the selected attributes are a good basis for explaining individual preferences, as the following example demonstrates.

Example:

In a pre-study 50 respondents indicated importance of 10 potentially relevant attributes on a 7-point scale (1 = not important, 7 = very important). Table 1 summarizes the results.

T a b l e 1

Results of a pre-study for selection of relevant attributes

Importance weights		Attribute number 1	2	3	4	5	6	7	8	9	10
Subject Number	1	5	4	5	7	4	1	1	2	1	2
	2	1	2	2	6	4	6	2	1	7	1
	.	.	.	.	.	.	.	.	.	.	.
	.	.	.	.	.	.	.	.	.	.	.
	50	2	1	5	7	6	3	1	5	2	6
Average		2.7	2.1	4.8	6.5	5.2	3.1	1.2	1.4	2.8	1.7

Taking the average importance weights across subjects the selection of - say - the 5 most important attributes leads to the attributes 4, 5, 3, 6 and 9. But these selected attributes in general do not represent the most important attributes of the individual respondent. For subject 1 the "important" attribute 1 is not in this standard list of attributes, for subject 50 the very important attribute 10 is "forgotten". So the method failed to select the relevant attributes for those persons. We do not think that this is an extreme example but rather a realistic one.

This problem arises if the condition of homogenity of relevant attributes across respondents [1] is violated and there are strong indications that in many cases this condition does not hold.

3. Conjoint Analysis with Individualized Sets of Relevant Attributes

The only way to avoid this problem is to use individualized sets of relevant attributes:

Select few but those attributes that are most relevant to the individual respondent.

This idea is not new, of course, in multiattribute preference modelling [8] but technical and economical reasons prevented its realization in conjoint analysis. Using the full-profile approach this requires to construct an individual set of test stimuli for each respondent. This is only possible if test stimuli are constructed by a computer. Consequently, we applied computer interactive interviewing to collect preference judgments. A portable micro-computer was used for this purpose. After knowing the respondent's most relevant attributes stimuli are generated automatically by the computer using a stored fractional factorial design [4].

In order to compare the predictive validity of the traditional method (standard list of relevant attributes for all respondents) and the method of individualized sets of relevant attributes an empirical study was conducted. As pointed out earlier different ways to measure importance can lead to different sets of relevant attributes. For this reason comparison of the two methods was done for two criteria for selecting important attributes: self-reported importance weights and importance weights derived from an information display board (IDB) task.

4. The Empirical Study

4.1. Study Design and Data Collection

Product category chosen for the study was videorecorder. Potentially relevant attributes were found by interviewing the cooperating manufacturer's managers, a retailer's sales personnel and by surveying point-of-purchase material. Additionally 10 consumers indicating intention-to-buy were interviewed. Besides price and brand name (which were not used in conjoint analysis) 24 potentially relevant product attributes were identified by this procedure. With exception of one three level attribute all attributes were conceptualized on two levels.

The sample for the study consisted of a total of 200 consumers who stated they intended to buy a videorecorder within the next year. This sample was split into four equal experimental groups as shown in Tab. 2.

Data were collected in a large shopping center in Regensburg. The procedural design can be seen in Fig. 2.

Table 2

Experimental design

		Importance measured by	
		self reported rankings	weights derived from IDB
Set of relevant attributes	individual list	group 1 n = 50	group 2 n = 50
	standard list	group 3 n = 50	group 4 n = 50

Figure 3 illustrates the computer interactive IDB-task. For techniqual reasons the number of attributes was restricted to 19 in this task. Respondents were instructed to choose one of the 8 available videorecorders. In order to perform the task properly the respondents got any information they wanted on attributes of a specific brand by simply typing in the letter of the alternative and the number of the attribute. At the end of the information search process the respondents had to indicate their preference and

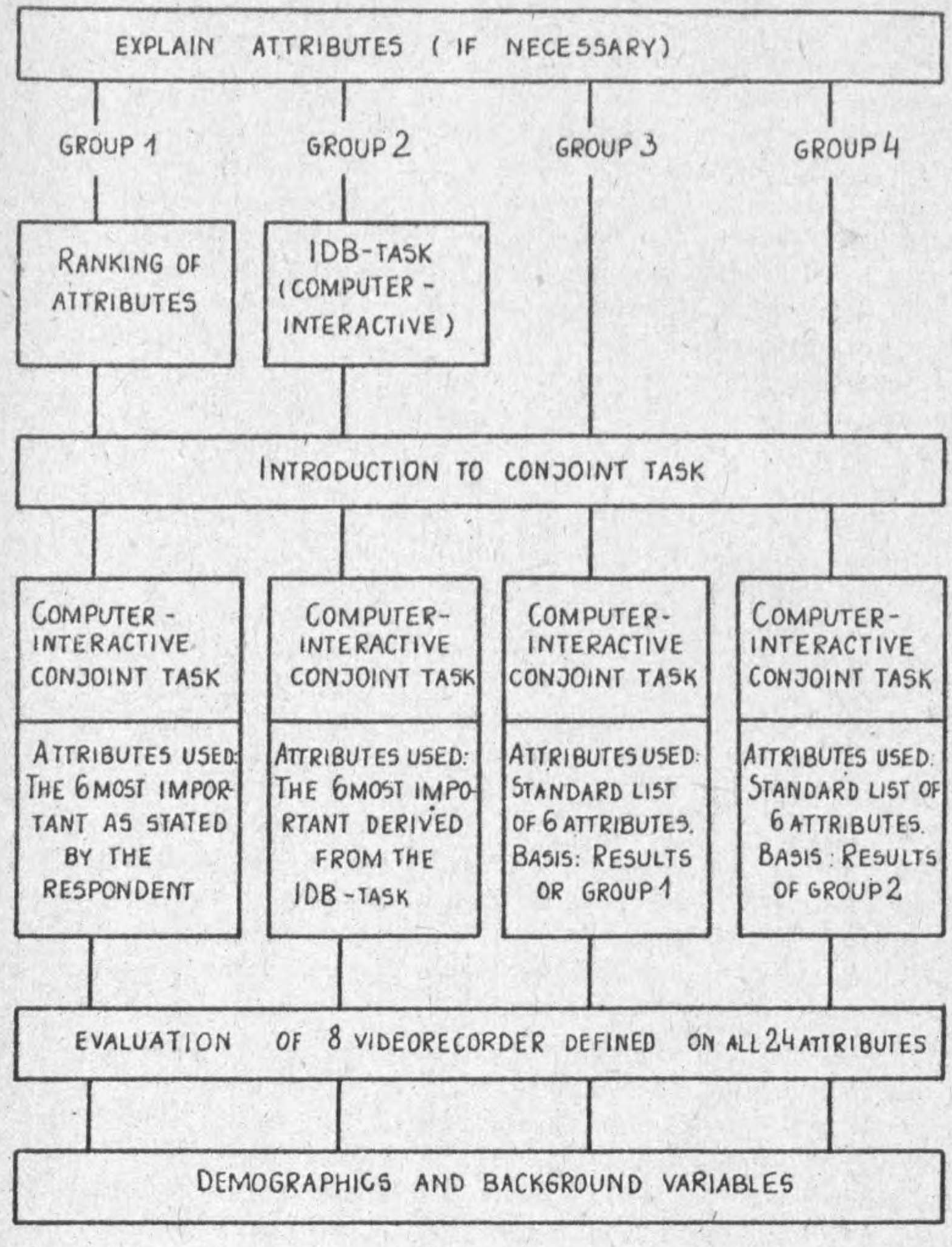

Fig. 2. The procedural design

VIDEORECORDER	ATTRIBUTES
A SONY SL - C 24	1 QUICK PICTURE SEARCH
B GRUNDIG 2280	2 REMOTE CONTROL
C PALLADIUM	3 SYSTEM
D JMR 2240	4 WARRANTY
E AKAI VS-1	5 TOP/FRONT LOADING
F PHILIPS VR2324	6 CAMERA CONNECTION
G TELEFUNKEN 950	7 TYPE OF TAPE COUNTER
H JVC 7200	8 TIMER: NUMBER OF PROGRAMS
	9 TIMER: NUMBER OF DAYS
	10 MONO/STEREO
	11 SLOW MOTION
	12 STILL PICTURE
	13 PROGRAMM STORAGE
	14 ADJUSTMENT OF PROGRAMS
	15 SIZE
	16 REWIND AUTOMATICALLY
GRUNDIG 2280 PRICE	17 HALF TAPE SPEED
	18 INSERT FUNCTION
2098.- DM	19 PRICE

TYPE IN LETTER OF ALTERNATIVE AND NUMBER OF ATTRIBUTE TO CHOOSE NEXT INFORMATION:

Fig. 3. The interactive information display board

the computer automatically calculated importance weights and selected the 6 most important attributes. Importance of an attribute was measured here by the number of information values chosen from that attribute [10].

Construction of test objects was done by the computer using the selected attributes and a pre-defined fractional factorial design. Respondents had to evaluate the objects pairwise. Figure 4 shows the video display of the conjoint task:

This scale forces the respondent to indicate direction as well as degree of preference and is called dollarmetric [11]. Altogether 35 pairs of videorecorders were presented by the computer in this manner.

VIDEORECORDER 1		VIDEORECORDER 2	
SYSTEM:	VHS	SYSTEM:	VIDEO 2000
REMOTE CONTROL:	NO	REMOTE CONTROL:	YES
WARRANTY:	12 MONTHS	WARRANTY:	6 MONTHS
SLOW SPEED:	YES	SLOW SPEED:	NO
MONO/STEREO:	MONO	MONO/STEREO:	MONO
CAMERA CONNECTION:	NO	CAMERA CONNECTION:	YES

IF PRICES ARE EQUAL: WHICH DO YOU PREFER?

ANSWER: LEFT RECORDER

VIDEORECORDER 1		VIDEORECORDER 2	
SYSTEM:	VHS	SYSTEM:	VIDEO 2000
REMOTE CONTROL:	NO	REMOTE CONTROL:	YES
WARRANTY:	12 MONTHS	WARRANTY:	6 MONTHS
SLOW SPEED:	YES	SLOW SPEED:	NO
MONO/STEREO:	MONO	MONO/STEREO:	MONO
CAMERA CONNECTION:	NO	CAMERA CONNECTION:	YES

IF THE PRICE OF THE LEFT RECORDER IS HIGHER:
HOW MUCH MORE ARE YOU READY TO PAY BEFORE YOU SWITCH PREFERENCE?

Fig. 4. The video display of the computer interactive conjoint task

Having finished this task the respondents of each group had to evaluate 8 pairs of videorecorders described on all 24 attributes (functions which were not present were not mentioned) and presented on cards using again the dollarmetric-scale. Figure 5 illustrates this task for one pair:

- Warranty 12 months	- Warranty 6 months
- System Betamax	- System VHS
- Weight 15 pounds	- Weight 15 pounds
- Size small	- Size small
- 1 recording within 7 days programmable	- 1 recording within 7 days programmable
- Front loading system	- Top loading system
- Program storage for 8 programs	- Program storage for 8 programs
- Remote control	- Every-day-function
- Quick picture search	- Quick picture search
- Still picture	- Still picture
- Memory-Function	- Slow motion
- Audio-Dubbing	- Fast motion

IF PRICES ARE EQUAL: WHICH DO YOU PREFER

IF THE PRICE OF THE LEFT (RIGHT) RECORDER IS HIGHER:
HOW MUCH MORE ARE YOU READY TO PAY BEFORE YOU SWITCH PREFERENCE?

Fig. 5. Evaluation of pairs of videorecorders defined on all 24 attributes

4.2. Data Analysis

To check whether dollarmetric-values can be interpreted as preference difference between right and left object ("interval theory") a test proposed by Hauser and Shugan [9] was applied first. If interval theory is confirmed ordinary least squares (OLS) regression is the appropriate technique for estimating the parameters of the preference function [9]. Consequently parameters of a part-worth model [7] were estimated only for respondents for which interval theory was supported (that is: whose 35 pairwise preference judgments showed not too many inconsistencies using the preference data of the computer interactive conjoint task and dummy regression (see [11] for a description). The estimated part-worth utilities for the levels of the attributes were the basis for predicting the preference differences (the dollarmetric values) for the

8 pairs of videorecorders defined on all 24 attributes (the prediction set). Pearson correlations between predicted and measured preference differences for these 8 pairs were computed for each respondent in order to get a measure for predictive validity.

4.3. Results

31 respondents (16%) had to be eliminated from further analysis because interval theory was rejected at the 1% - significance level. To summarize predictive validity for the remaining subjects the mean pearson r was obtained by averaging the correlations across subjects using Fisher's r to z transformation. The mean correlations are presented in Tab. 3.

Table 3

Predictive validity (average pearson correlations between predicted and measured dollarmetric-values for 8 pairs of videorecorders defined on all 24 attributes)

		Importance measured by	
		self reported rankings	weights derived from IDB
Set of relevant attributes	individual list	0.893 group 1	0.892 group 2
	standard list	0.833 group 3	0.880 group 4

One should observe that conjoint analysis using individual sets of relevant attributes outperforms traditional conjoint analysis using a standard list of attributes for both measures of importance. To test whether differences are significant a t-test was carried out for each importance measure separately (again using Fisher's z-values instead of r). If self-explicated importance is the basis for selecting relevant attributes (comparison of group 1 and group 3) the effect of using the individual relevant attributes instead of attributes which are "on average most important" was found to be significant at the 5% significance level. Comparing groups 2 and 4 on the other side where attribute importance was measured by the IDB no significant ($\alpha = 5\%$) difference was observed between predictive validity of conjoint analysis with individualized sets of relevant attributes and traditional conjoint analysis.

Thus in this study a significant increase in predictive power was observed only partly; results do not allow an unequivocal answer to the question if there is a better prediction of preferences with individualized sets of relevant attributes.

A reason for the partial lack of significance in increase of predictive power may be the fact that there was one attribute ("system") which had a dominant influence on preference for almost all respondents. In respect to the most important attribute the sample was therefore quite homogeneous. As a consequence, the necessary condition for a substantial increase in predictive power - heterogenity of relevant attributes between respondents - was true only for the rest of the attributes.

To evaluate predictive power of conjoint analysis with individual sets of relevant attributes further studies - based on the approach presented in this paper - have to be conducted. Taking into consideration the number of commercial applications of conjoint analysis the research question of this paper is of enormous practical relevance. We assume that individualized sets of attributes are the more fruitful the more heterogeneous the preference structures of the relevant respondents are, that is the more heterogeneous the set of relevant attributes is.

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CZY MOŻLIWE JEST
UDOSKONALENIE PRZEWIDYWANIA PREFERENCJI KONSUMENTÓW
NA PODSTAWIE ZINDYWIDUALIZOWANEGO ZESTAWU CECH PRODUKTÓW?

Artykuł zawiera prezentację metodologii badań polegającą na przejściu od zawężających założeń mówiących iż "właściwe czynniki eksperymentalne (cechy produktu) są ilościowo ograniczone i stałe

wśród respondentów" (17) do założeń bardziej realistycznych - twierdzących iż choć liczba czynników eksperymentalnych jest niewielka, to różnią się one istotnie między respondentami. Po rozwinięciu elementów prezentowanego podejścia, zostały przeprowadzone badania empiryczne w celu pomiaru wzrostu wartości analizy preferencji opartej na właściwym każdej jednostce zestawie cech, w odróżnieniu od zestawu standardowego.

Rezultaty tych badań nie pozwalają udzielić jednoznacznej odpowiedzi na pytanie postawione w tytule artykułu, gdyż istotne polepszenie wartości przewidywanych preferencji stwierdzone jedynie dla niektórych cech. Dalsze badania muszą być kontynuowane w celu rozwiązania tego problemu.