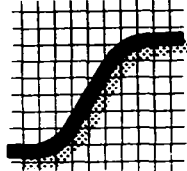


Note



THE FACTOR STRUCTURE OF MULTIDIMENSIONAL RESPONSE TO MARKETING STIMULI: A COMPARISON OF TWO APPROACHES

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Factor Analysis is commonly used to reveal the structure underlying the multiple attributes that describe marketing stimuli. This paper provides a theoretical investigation and an empirical comparison of two approaches to Factor Analysis that are based on two different sources of variation in the input data. The "Among" Analysis is based on variation across marketing stimuli, while the "Within" Analysis is based on variation across individuals responding to the same marketing stimulus. We identify conditions under which one approach is superior to the other. If both approaches are applicable, we recommend the use of the "Total" analysis that pools the variation across stimuli and individuals. An empirical study, in the context of consumers' cognitive response to ads, shows that the Among Analysis results can be seriously distorted by differential familiarity with the ads so that it is important to partial out the spurious effects of familiarity.

(Factor Analysis; Perceptual Mapping; Product Positioning; Reduced Space Methods)

Introduction

Consumers' responses to marketing stimuli, such as products or advertisements, are typically multidimensional. The multiple response variables could, for instance, be the attributes of a brand in a product class or the rating scales designed to evaluate an ad. The identification of the structure of the variables is often of major interest for direct or indirect reasons. The direct interest is to understand the underlying constructs (latent variables) that form the basis of the multidimensional response. The indirect interest is to parsimoniously represent the many variables in terms of a few dimensions so that the marketing stimuli can be represented in a reduced dimensional space for further analysis.

Factor analysis is a commonly used method for identifying the structure of multidimensional responses. The rotated factor loadings matrix summarizes the structure by indicating which variables associate primarily with which factors. Based on the notion of "simple structure" (Thurstone 1947), we use the word "structure" to denote the *identification for each variable of the factor with which it is primarily associated*. By

0732-2399/89/0801/0078\$01.25

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defining structure in this manner. We are deliberately deemphasizing the exact magnitudes of the factor loadings. The reason for this deemphasis is that the reliability (and hence communality) of a variable may change from one measurement context to another (e.g., when averages are obtained from samples of different sizes), thereby resulting in changes in the factor loadings even though the basic underlying structure relating the variables to the factors may remain essentially unchanged.

Methods for Identifying Factor Structure

By collecting multidimensional responses from a sample of individuals for the *same* stimulus, the data may be represented as a matrix of respondents by variables. By collecting data on multiple stimuli, we obtain a data box of respondents by variables by stimuli.

Since our interest is on the structure of the variables, we can factor analyze correlation matrices derived from the sum of squares and cross products matrices of the N variables. The matrix of total sum of squares and cross products can be decomposed by the relationship (Cooley and Lohnes 1971, p. 226):¹

$$T = W + A \quad \text{where} \quad (1)$$

$T = (N \times N)$ matrix of *total* sum of squares and cross products,

$W = (N \times N)$ matrix of *within* sum of squares and cross products, and

$A = (N \times N)$ matrix of *among* (or between) sum of squares and cross products.

Depending on whether we factor analyze the correlation matrix corresponding to T , W or A , we have the *Total Analysis*, *Within Analysis* and *Among Analysis*, respectively.

The common practice of factor analyzing the correlation matrix obtained from the stimuli by variables matrix of average scores (the average being taken over the individuals) is nearly the same as the Among Analysis. (The results will be exactly the same if the number of individuals evaluating the stimuli remains constant across stimuli.) Thus the Among Analysis concentrates on variability among the stimuli. The Within Analysis, on the other hand, concentrates on the variability among individuals. To see this, we first note that the matrix W may be further decomposed into

$$W = W_1 + W_2 + \dots + W_S \quad (2)$$

where W_j denotes the within sum of squares and cross products matrix corresponding to the data obtained for stimulus j , $j = 1, 2, \dots, S$ (see footnote 1). Thus, W denotes the within matrix averaged over the S stimuli (ignoring the multiplicative constant of $1/S$). Consequently, the Within Analysis factor analyzes the correlation matrix obtained from the individuals by variables data matrix so that the structure obtained is based on the variability among individuals for the same stimulus.

¹ Let X_{ijk} denote the i th respondent's evaluation of the j th stimulus on the k th variable. Let R respondents evaluate S stimuli on N variables so that X is an $R \times S \times N$ data box. Let m also denote a variable (k may or may not equal m). The (k, m) th element of the T , W and A matrices are given by the expressions below where $k = m$ denotes sum of squares and $k \neq m$ denotes a cross-product:

$$T_{km} = \sum_{j=1}^S \sum_{i=1}^R (X_{ijk} - \bar{X}_{..k})(X_{ijm} - \bar{X}_{..m}),$$

$$W_{km} = \sum_{j=1}^S [\sum_{i=1}^R (X_{ijk} - \bar{X}_{.jk})(X_{ijm} - \bar{X}_{.jm})],$$

$$A_{km} = R [\sum_{j=1}^S (\bar{X}_{.jk} - \bar{X}_{..k})(\bar{X}_{.jm} - \bar{X}_{..m})].$$

The dots indicate the indices over which the averages \bar{X} are computed. These formulae can be generalized to the case where the number of respondents evaluating a stimulus differs across stimuli (Cooley and Lohnes 1971, pp. 224–226).

Theoretical Comparison of the Among and Within Approaches

From equation (1) it is clear that there is no necessary relationship between the matrices W and A so that from purely a mathematical point of view the structures determined by the Within and Among Analysis could, in principle, be very different from each other.

The structure underlying an individual's multidimensional response may be hypothesized to result from the following considerations:

(a) Semantic similarity: A subset of variables in the instrument are basically different wordings of the same construct. For instance, we would expect "frequency of repair" and "reliability" of cars to be highly (negatively) correlated.

(b) Cognitive consistency based on perceived causal relationships between constructs: Two variables may be based on two different constructs perceived to be directly or indirectly causally related. For instance, "size" and "gas mileage" of cars, although referring to two different constructs, are likely to be perceived as causally related. Variables which have a "part-whole" relationship will also exhibit correlation due to perceived causation. For instance, "gas mileage" and "operating costs" are likely to be correlated.

(c) Cognitive association based on ecological correlation: Two variables may be based on two constructs which have no perceived causal relationship per se, but exhibit an ecological (environmental) correlation. For instance, a respondent may associate "sportiness" of cars with "European" if most sports cars are made in Europe.

It is assumed that the structure resulting from considerations (a)–(c) above is homogeneous across individuals. If there is reason to expect systematic differences in the structure across subgroups of respondents (e.g., Americans vs. Europeans), the Within, Among, and Total Analysis should be conducted separately for each subgroup.

As explained earlier, the Within Analysis may be thought of as based on the correlations obtained from a matrix of individuals' ratings of a stimulus on several variables. Thus two variables X and Y will be positively correlated if the individuals who rated the stimulus to be high (low) on X also rated it to be high (low) on Y . This is likely to happen if X and Y are related on the basis of any of the considerations (a)–(c) above.

The Among Analysis is based on the stimuli by variables matrix of average scores. Considerations (a)–(c) are again likely to influence the pattern of correlations. For instance, if we consider two positively related variables X and Y which are really two different wordings of the same construct, then if a stimulus gets a high (low) average score on X , it is also likely to obtain a high (low) average score on Y . We conclude that the Within and Among analyses are likely to reveal similar structures. This is not a necessity, however, and as explained below, several issues and potential problems may lead the analyses to yield different results. (See Table 1 for a summary.)

Impact of Ecological Correlation

The pattern of correlations in the among Analysis can be unduly influenced by ecological associations. The Within correlation is likely to be less influenced by ecological association if the variables are perceived as not causally related. For instance, if in practice, "eye catching" ads are mostly uninformative, the correlation between "eye catching" and "informative" will be strongly negative in the Among Analysis. However, respondents, may perceive no necessary causal association between these two constructs so that in the Within Analysis the magnitude of the negative correlation is likely to be considerably smaller. The Within Analysis in this case more closely reflects the cognitive structure of the respondents.

In the context of multiattribute evaluations of brands in a product class, ecological correlations may result from the particular way competing brands are currently posi-

TABLE I
Issues and Potential Problems in Within/Among Analysis

Issue	Within Analysis	Among Analysis
Impact of ecological (environmental) correlation	Small.	Potentially excessive.
Number and nature of stimuli	Minimal problems.	Potentially serious problems if the stimuli are few in number and/or not representative.
Effects of differential familiarity	Could be corrected if a measure of familiarity is available. If left uncorrected, problem is likely to be less serious than would be the case for Among Analysis.	Could be corrected if a measure of familiarity is available. If left uncorrected, differential familiarity can create serious problems.
Homogeneity of structure across stimuli	Needs to be tested. If structures vary substantially across stimuli, the stimuli may be clustered based on similarity of structure and analysis repeated for each cluster.	Problem is not transparent, but exists.
Response tendency artifacts	Could, in general, be corrected for. However, if each individual rates only a single stimulus (or very few stimuli), correction is not feasible so that potentially serious problems can arise.	Minimal problems.
Absence of variation	If individuals do not differ in their evaluations of a stimulus on a variable, that variable will disappear from the analysis.	If the average evaluations on a variable do not vary across stimuli, that variable will disappear from the analysis.

tioned. The Within Analysis may prove more useful for identifying potential new product ideas (Shocker and Srinivasan 1979) since it is less constrained by the set of current offerings. For instance, if in the sample of cars under consideration, "sportiness" and "expensiveness" tend to be highly positively correlated, the Among Analysis would collapse the two variables into a common dimension. For the reasons advanced earlier, the correlation may be smaller in the Within Analysis so that the two variables do not collapse into a common dimension. This permits subsequent analysis to identify a sporty looking but less expensive car as a potential new product.

Number and Nature of Stimuli

The number of stimuli used in marketing studies tends to be much smaller than the number of respondents so that correlations in the Among Analysis are very sensitive to sampling fluctuations and sampling bias. For instance, if as few as ten stimuli are used in a study, and the true correlation between variables is zero, 95% of the sampled correlations fall in the -0.63 to $+0.63$ range. Further, the correlations in the Among Analysis can be strongly influenced by the lack of representativeness of the stimuli used in the data collection. For instance, the correlation between "size" and "expensiveness" of cars is likely to be positive if the sample consisted of only American cars, but may become negative if the sample were to consist of large American cars as well as expensive European imports. The correlation in the Within Analysis, however, is likely to stay positive in both cases.

Differential Familiarity

The pattern of correlations in the Among Analysis can get distorted by the respondents' differential familiarity with the stimuli. For instance, more familiar stimuli may

get evaluated more favorably than the less familiar ones, introducing a "halo effect" bias in the obtained correlations. This problem is likely to be less in the Within Analysis, since in many marketing contexts, the variation of familiarity tends to be more substantial across stimuli than across respondents. If a measure of familiarity is available, distortions created by differential familiarity could be corrected by partialling out its effects in the analysis (see empirical section).

Homogeneity of Structure Across Stimuli

The Within Analysis assumes the structure to be homogeneous across stimuli so that the averaging implied by equation (2) is meaningful. Homogeneity is a reasonable assumption since the structure is based on the relationship between variables and constructs and not on the stimuli *per se* (see (a)–(c) above). However, there is a distinct possibility that homogeneity will not obtain across stimuli (Osgood, Suci and Tannenbaum 1975, p. 176). Howard and Sheth (1969, p. 213) argue that if the structure is different for different brands, ". . . there exists sufficient evidence . . . to warrant the conclusion that the various brands are not really elements of the same product class from the buyers' point of view. . . ." In any event, the researcher should examine whether the structures generated by the W_j matrices are similar across stimuli prior to conducting an analysis based on the W matrix. Otherwise, the stimuli could be clustered on the basis of similarity of structure and the Within Analysis repeated separately for each cluster.

The issue of homogeneity of structure exists in the context of Among Analysis but is not transparent because the correlation is calculated over the entire sample of S stimuli and not over subsets of stimuli.

Response Tendency Artifacts

To the extent that some individuals have a response tendency to use higher values on every scale and some others a tendency to use lower values on every scale, a positive bias exists on the correlation between any two variables. To remove this bias, each individual's data on each variable can be standardized to have a zero mean over the stimuli. Such an adjustment for response tendency is possible only if each individual rates a representative subset of stimuli on each variable, or when some independent measure of response tendency is available. If each individual rates only a single stimulus, no such adjustment is possible, so that the Within Analysis is likely to yield biased results.

Response tendencies have no effect on the correlations in the Among Analysis. If the set of individuals remains the same for each stimulus, the average value (computed over individuals) for every stimulus gets shifted by the same amount and this will have no effect on the correlations computed over the stimuli. (See Dillon, Frederick and Tangpanichdee 1985 for a more general discussion of the effects of preprocessing the original data arrays (e.g., row/column normalization, standardization, centering, etc.) on the results obtained by factor analysis.)

Absence of Variation

The Within Analysis requires variability across individuals in evaluating a stimulus on every variable. Attributes such as "filter vs. nonfilter" in cigarettes or "foreign vs. domestic" in automobiles may get exactly the same rating from each individual for a specific stimulus so that the lack of variation will make such important attributes disappear from the factor analysis. Thus the Within Analysis will break down for attributes for which there is very high perceptual homogeneity among individuals. Similarly, if the stimuli used in the sample are such that the average scores on a variable are roughly the same for each stimulus, then that variable would disappear from the Among factor analysis.

Neither the Within, nor the Among approach is unconditionally superior. The issues summarized in Table 1 guide us in choosing the more appropriate analysis mode in any specific context. If a large number of stimuli are used so that sampling errors in the correlations are small, the stimulus set is representative of the population of stimuli from the respondents' point of view and a measure of familiarity is available so that the correlations can be adjusted for familiarity, then the Among Analysis would be appropriate. The Within Analysis would be appropriate if respondents rated most of the stimuli so that adjustments can be done to minimize response tendency artifacts. It should be re-emphasized that the Within Analysis has the advantage of not being excessively influenced by the ecological correlations present in the set of stimuli used in the study.

Overall, we believe that the Within Analysis deserves more attention than allowed by the current marketing practice of rather common use of Among Analysis, which may in part be due to the ready availability of packaged programs for Among Analysis. (One needs merely to submit the matrix of stimuli average scores to a factor analysis program.) The Within Analysis, on the other hand, needs much greater computational effort. (The adjustment for response tendencies, the homogeneity check, the pooling of matrices as per equation (2) and the computation of the correlation matrix corresponding to W require effort and, to our knowledge, no packaged programs are readily available.) In situations where each respondent rates only a few stimuli, response tendency artifacts may overwhelm the Within Analysis so that Among Analysis would be more appropriate.

For the reasons summarized in Table 1, it is clear that there are situations where it is better to concentrate on the variation due to individuals alone and do a Within Analysis; and there are other situations where it is better to concentrate on the variation due to stimuli alone and do an Among Analysis. It is therefore not appropriate to blindly pool both sources of variations and conduct a Total Analysis simply because it utilizes all the information. *If, however, the situation as indicated in Table 1 is such that both sources of variation are appropriate, we can increase the reliability of the results by conducting a Total Analysis,² i.e., factor analyze the correlation matrix derived from T .* Alternatively, Three-Mode factor analysis (Levin 1965, Belk 1974) (or the PARAFAC procedure by Harshman 1970) is suitable as a method of pooling the Within and Among Analyses, if the sample of individuals rating the stimuli remains the same across stimuli. However, if in a specific situation the considerations in Table 1 strongly favor one method (Within or Among), we feel that Total Analysis and Three-Mode Analysis are less appropriate since their results will be confounded by the biases and problems present in the less desirable method.

Yet another method of taking into account the variation across individuals and stimuli is the so called "Wish technique" (named after Michael Wish of Bell Laboratories). For each individual, the Euclidean distances between stimuli profiles are computed and analyzed by INDSCAL (Carroll and Chang 1970) resulting in a plot of the stimuli on the underlying dimensions. This method has the advantage of taking into account individual differences expressed in terms of differential weights for the underlying dimensions. A further advantage is that the obtained solution is unique so that there is no need for rotation. However, this method is, in effect, a Total Analysis since it considers variation among stimuli and individuals. Consequently, this method is not appropriate in situations when it is better to concentrate on variations due to individ-

² The Total Analysis is more conveniently done by stacking up the responses of individuals (on the different brands) on top of each other, thus obtaining for each variable a vector of length equal to the number of individuals times the number of brands (Hauser and Urban 1977).

An Empirical Comparison

Data

The data were obtained from a Consumer Jury pretest of 50 advertisements. Each respondent stated his or her opinions concerning an ad along 16 evaluative dimensions presented in the form of rating scales. Fifty full-page ads were selected from two issues of two leading women's weeklies so as to represent a variety of product classes, communication approaches and format characteristics. Respondents were mostly unfamiliar with 15 of the 50 ads. Of these 15 ads, some were for largely known brands and others were for largely unknown brands.

The data were obtained through a questionnaire mailed to a random sample of housewives from a consumer studies panel. Each respondent was asked to rate 10 ads on 16 six-level bipolar scales. To minimize halo effects, all 10 ads were rated on a scale before moving on to the next scale. The order of presentation of stimuli and questions were systematically rotated. The rating scales included relevant response dimensions relating to both the "communication process" dealing with the individual's response to the ad itself and the "decision process" dealing with the response to the object (brand) of communication (Vanden Abeele and Butaye 1978). The response rate to the survey approximated 90% for a single wave, yielding in excess of 170 respondents for each ad under study. This corresponds to a total sample size of about 850 respondents since each respondent rated only 10 of the 50 ads.

In order to minimize response tendency artifacts, the data were standardized so that for each respondent and for each variable the mean and standard deviation over the ads rated would be 0 and 1, respectively.

All factor analyses used the common factor model with communalities determined by an iterative procedure (Green 1978, p. 395). Kaiser's "eigenvalue greater than one" rule was employed to determine the number of factors. The factor solutions were Varimax rotated.

Results of Within Analysis

The first part of Table 2 shows the loadings on the three rotated factors for the Within Analysis. To display the structure of the multidimensional response, for each scale the factor on which its loading is the largest is underlined. (Other loadings within 0.05 of the maximum loading are also underlined.)

For the Within Analysis, Factor 3 appears to connote "information transmission", Factor 2 "visual impact" and the associated memorability and Factor 1 an "overall attitude towards the ad and brand advertised."

Homogeneity of Structure Among Ads

In order to check whether the factor structures for the 50 ads are similar, a factor analysis with three factors was carried out for the Within Correlation matrix for each ad. Homogeneity of structure was evaluated by examining whether the factor structures for the individual ads were consistent with the structure obtained by the pooled Within Analysis. A simple matching test³ indicated that there is a substantial amount of homogeneity among the structures found for the 50 ads.

³ The test involved counting the number of "matches" in each separate Within Analysis with the pooled Within Analysis. If the factor on which a variable had its highest loading is the same on both results, then there is a "match" on that variable, otherwise there is no match. The total number of matches aggregated over the 16 variables and 50 ads was 78% of the maximum possible number of matches. Given that the Within Analysis results for each of the ads were not rotated to maximum congruence with the pooled Within Analysis, the test statistic of 78% provides a conservative account of the extent of homogeneity of the Within Structures. Full details of the test procedure are available upon request.

TABLE 2

Loadings on Three Factors and Communalities^a in the Within, Among and Total Analyses^b

Rating Scale ^c	Within				Among				Total			
	I	II	III	Comm.	I	II	III	Comm.	I	II	III	Comm.
1. Eye Catching	15	<u>69</u>	13	52	-01	<u>92</u>	17	87	11	<u>78</u>	03	62
2. Pleasing	19	<u>65</u>	21	50	05	<u>88</u>	04	79	15	<u>74</u>	11	58
3. New Learning	06	05	<u>45</u>	21	26	-20	<u>-88</u>	89	02	-03	<u>64</u>	41
4. Interesting	33	31	<u>58</u>	55	<u>90</u>	17	-32	94	45	29	<u>54</u>	58
5. Informative	28	14	<u>42</u>	27	<u>84</u>	-21	-14	77	<u>48</u>	-03	41	41
6. Credible	<u>50</u>	09	25	32	<u>89</u>	01	-05	79	<u>60</u>	05	28	44
7. Attention Getting	<u>51</u>	37	36	54	<u>82</u>	43	-32	95	<u>52</u>	40	40	58
8. Easy to Remember	<u>47</u>	<u>49</u>	17	49	<u>52</u>	<u>71</u>	41	94	<u>51</u>	<u>57</u>	04	58
9. Connects to my Life	<u>57</u>	21	18	40	<u>75</u>	10	49	81	<u>67</u>	21	04	49
10. Makes me Curious	<u>63</u>	22	30	54	<u>85</u>	27	03	80	<u>63</u>	27	27	55
11. Fav. Product Attitude	<u>69</u>	27	30	64	<u>92</u>	34	12	98	<u>72</u>	32	25	69
12. Clear	<u>48</u>	29	21	36	<u>85</u>	12	33	85	<u>64</u>	23	13	48
13. Buying Influence	<u>73</u>	21	18	62	<u>87</u>	31	31	95	<u>76</u>	27	12	67
14. Product Recognition	<u>40</u>	31	02	26	37	45	<u>60</u>	70	<u>47</u>	38	-16	39
15. Good Product Image	<u>40</u>	<u>36</u>	07	29	48	<u>61</u>	46	81	<u>44</u>	<u>41</u>	-04	37
16. Good Product Comments	<u>64</u>	13	14	44	<u>88</u>	12	28	87	<u>70</u>	14	10	52
Explained variance (%)	<u>53</u>	<u>28</u>	<u>19</u>	43	<u>59</u>	<u>24</u>	<u>17</u>	86	<u>55</u>	<u>29</u>	<u>16</u>	52
	100				100				100			

^a Decimals omitted^b Underlining denotes the factor on which the loading is the maximum for that variable. Other factors which have a loading within 0.05 of the maximum are also underlined.^c Each rating was made on a six-level bipolar scale. Items were worded in the format "This ad (is) (evokes) . . ."

Results of Among Analysis

The second part of Table 2 shows the factor structure obtained in the Among Analysis. The communalities and loadings are much higher than in the Within Analysis, since (more reliable) averages are used as the data rather than raw scores (Johnston 1972, pp. 231-232). The Among Analysis also results in a three-factor solution by the Kaiser criterion. In both analyses the second factor connotes "visual impact" and the associated memorability. However, the other two factors are quite different. The first factor combines items which connote "information transmission" on the one hand and "cognitive response" to the ad on the other, while also including most of the "decision process" variables. The third factor associates lack of new learning with recognition, implying an element of "prior familiarity" with the message.

The Among results are thus qualitatively rather different from the Within Analysis. The difference is particularly striking in the third factor. While the Within Analysis appears to yield an "information transmission" factor, this construct gets confounded with another and appears as Factor 1 in the Among Analysis.

Reconciling the Two Analyses

As discussed earlier, an undesirable aspect of the Among Analysis is that its correlations may get distorted by the differential familiarity with the ads. Consequently, by partialling out this effect, the results should be more similar in the two analyses. Fortunately, data had also been collected on the respondents' prior familiarity with the ads on a six-level bipolar scale. Thus it was possible to reconstruct the Within and Among correlation matrices after partialling out the effects of prior familiarity. This

TABLE 3

Loadings on Three Factors and Communalities^a in the Within, Among and Total Analyses
After Partialling out the Effect of Familiarity with the Ads^b

Rating Scale ^c	Within				Among				Total			
	I	II	III	Comm.	I	II	III	Comm.	I	II	III	Comm.
1. Eye Catching	11	<u>68</u>	13	49	-08	<u>95</u>	-06	91	09	<u>77</u>	04	60
2. Pleasing	15	<u>64</u>	21	47	12	<u>90</u>	-10	84	13	<u>73</u>	13	57
3. New Learning	05	03	<u>44</u>	20	25	-10	<u>93</u>	94	00	-05	<u>63</u>	40
4. Interesting	27	29	<u>58</u>	50	64	13	<u>70</u>	92	32	27	<u>59</u>	52
5. Informative	24	12	<u>40</u>	24	49	-28	<u>68</u>	79	37	-07	<u>43</u>	33
6. Credible	<u>40</u>	07	22	22	<u>79</u>	-06	42	81	<u>46</u>	00	31	31
7. Attention Getting	<u>46</u>	36	35	47	<u>62</u>	38	<u>61</u>	89	<u>42</u>	<u>39</u>	<u>44</u>	52
8. Easy to Remember	41	<u>49</u>	15	43	25	<u>90</u>	19	91	45	<u>57</u>	05	53
9. Connects to my Life	<u>46</u>	19	14	26	<u>77</u>	-02	02	59	<u>47</u>	20	06	26
10. Makes me Curious	<u>57</u>	20	27	43	<u>67</u>	23	48	74	<u>51</u>	26	31	43
11. Fav. Product Attitude	<u>63</u>	26	28	54	<u>87</u>	31	39	99	<u>62</u>	32	30	57
12. Clear	<u>41</u>	28	19	28	<u>63</u>	03	48	63	<u>54</u>	20	15	35
13. Buying Influence	<u>67</u>	19	14	50	<u>77</u>	28	46	88	<u>67</u>	25	15	54
14. Product Recognition	<u>32</u>	<u>31</u>	00	19	-11	<u>53</u>	01	29	<u>37</u>	<u>38</u>	-17	31
15. Good Product Image	<u>32</u>	<u>35</u>	04	23	30	<u>70</u>	-01	57	<u>36</u>	<u>40</u>	-04	30
16. Good Product Comments	<u>51</u>	10	09	28	<u>89</u>	00	25	84	<u>53</u>	11	11	30
Explained variance (%)	<u>47</u>	<u>32</u>	<u>21</u>	36	<u>44</u>	<u>30</u>	<u>26</u>	78	<u>44</u>	<u>34</u>	<u>22</u>	43
	100				100				100			

^a Decimals omitted

^b Underlining denotes the factor on which the loading is the maximum for that variable. Other factors which have a loading within 0.05 of the maximum are also underlined.

^c Each rating was made on a six-level bipolar scale. Items were worded in the format "This ad (is) (evokes). . ."

was done by replacing each of the original correlations by the corresponding partial correlations taken with respect to the familiarity variable.⁴

The recomputed factor analysis results are presented in Table 3. The Within Analysis results remain essentially the same in going from Table 2 to Table 3, confirming our speculation that the effects of differential familiarity are less serious for the Within Analysis. However, the Among Analysis results undergo a rather dramatic change and become roughly the same as the Within Analysis.

The fact that two different aspects of the information contained in the data box (viz., the Within and Among variation) lead to essentially the same structure provides convergent validity to the empirical results of both the Within and Among Analyses.

Results of the Total Analysis⁵

The last part of Table 2 presents the structure obtained by factor analyzing the correlation matrix formed from T (total sum of squares and cross products matrix).

⁴ Augment the X data box (see footnote 1) to include the familiarity variable. Compute the $(N + 1) \times (N + 1)$ matrix T and the corresponding correlations matrix R. Let k and m denote two of the N variables and let f denote the familiarity variable. Given the correlations R_{km} , R_{kf} and R_{mf} the partial correlation

$$R_{km.f} = \frac{R_{km} - R_{kf}R_{mf}}{\sqrt{(1 - R_{kf}^2)(1 - R_{mf}^2)}}$$

The partial correlations based on the matrices W and A are similarly defined.

⁵ Three-Mode Factor Analysis is not appropriate in this empirical study, since the sample of respondents varies across the ads.

The results are similar to those in the Within Analysis, though not quite as "clean". Differences are, as expected, in the direction of the Among Analysis.

The results of the Total Analysis after partialling out the effect of familiarity are presented in the last part of Table 3. The structure is virtually the same as in the Within Analysis as may be expected from the closeness of the Within and Among analyses after partialling out the effects of prior familiarity.

Conclusions from the Empirical Study

The substantial changes in the structures identified by the Among Analysis between Tables 2 and 3 confirm that differential familiarity with the stimuli, if not corrected for, can create serious problems for the Among Analysis. The stability of the structures identified by the Within Analysis in Tables 2 and 3 indicates that the Within Analysis is considerably less affected by differential familiarity in this empirical context.

Table 1 suggests that, in the present empirical study, the Among Analysis is appropriate since the number of stimuli is large (50 ads) and since the effects of differential familiarity could be partialled out. The Within Analysis is appropriate since response tendency artifacts could be removed. The conclusion that both the Among and Within analyses are appropriate is consistent with the similarity of the structures identified in Table 3 by these two methods. Given that both methods are appropriate, the structure identified by the Total Analysis in Table 3 provides a more reliable estimate of the results of the Within and Among analyses. A logical next step would be to collect new data and perform a confirmatory factor analysis (Heeler, Whipple and Hustad 1977) to test out the structure identified by the Total Analysis in Table 3.

Implications for Market Research

Several approaches have been proposed for identifying the "reduced-space" in multiattribute modeling approaches to product concept evaluation and generation (Shocker and Srinivasan 1979). These include Within Analysis (Howard and Sheth 1969, p. 212), Among Analysis (many commercial applications tend to be of this type) and Total Analysis (Hauser and Urban 1977). The number of stimuli used in these studies is typically small (often less than a dozen). This, together with the issue of ecological correlation, suggests that the Within Analysis may often be more appropriate than Among and Total Analyses. In this context, it may be worthwhile to point out that the three-mode factor analysis (Belk 1974) is similar to a Total Analysis, and the procedure MDPREF (Green and Wind 1973, p. 326) amounts essentially to an Among Factor Analysis. The application of multidimensional scaling of similarity judgments to generate the reduced space (Stefflre 1972, Urban 1975) is an Among Analysis since it concentrates on variation among stimuli. INDSCAL (Carroll and Chang 1970) allows for individual differences in the weighting of dimensions, and is a Total Analysis since the underlying dimensions are derived based on variation among stimuli and individuals. It may be better to do an individual differences multidimensional scaling of the variables themselves, i.e., respondents could be asked to state the extent of similarity/dissimilarity of pairs of variables and these data used to provide a reduced space representation of the variables. This approach is promising since it concentrates directly on the individuals' cognitive structure of the multidimensional response variables. Multiple Discriminant Analysis (Johnson 1971) maximizes the ratio of among to within dispersion and hence may again have the problems of the Among Analysis. Furthermore, to maximize the above ratio, multiple discriminant analysis tends to deemphasize variables which have a large within variance. Such a deemphasis is not desirable; in fact, a larger within variance provides a better opportunity to discover the cognitive structure via the Within Analysis. For a detailed evaluation of different

methods for building perceptual product spaces, see Hauser and Koppelman (1979) and Dillon, Frederick and Tangpanichdee (1985).

In the context of identifying the structure of variables representing consumers' multidimensional response to ads, the number of stimuli (ads) can be made large and representative. As in the empirical study, if data on familiarity are also collected, the effects due to differential familiarity can be partialled out. Consequently, both the Within and the Among analysis can be appropriate in this context so that their results can be pooled and the structure identified by the Total Analysis or by Three-Mode Factor Analysis.⁶

Acknowledgements. The authors are grateful to the publishers of *Rijk der Vrouw/Femme d' Aujourd'hui* for providing the list of their consumer studies participants, used as the sampling frame in this study. The authors also thank the Area Editor, three reviewers, and Professor Allan D. Shocker for their comments on an earlier version of this paper.

⁶ This paper was received December 1987 and has been with the authors 1 month for 1 revision.

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