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A Customer-Oriented Approach for Determining Market Structures

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A framework for market analysis based on customer perceptions of substitutability-in-use is presented. An empirical application in the financial/banking services market is used to illustrate that when product preferences are dependent on the use/consumption context (especially relevant when products have multiple uses), situational variables can help predictive ability, and hierarchical clusters (requiring exclusive group membership) may be misleading. Additionally, it is shown that interactions among situation, product, and person factors may be more managerially meaningful than the main effects.

Introduction

THE understanding of customer choice and competitive relationships in the marketplace has been the focus of considerable research in marketing and social sciences. Most of this research is based on the paradigm that choice is a function of product attributes and customer characteristics. The premise of benefit segmentation, for example, is that people seek benefits that products provide rather than products per se, and that different (groups of) individuals may desire varying (sets of) benefits. However, products and customers do not exist in a vacuum. Both are embedded in an environment. The available evidence indicates that the intended or anticipated use of the product, the functions to be served, the application/consumption context, or in general the "usage situation" influences the choice among products/brands and, consequently, substitutability (see Srivastava 1981 for a comprehensive review). Over a period of time customers may develop sets of products for consideration based upon the perceived appropriateness of their functional attributes for the intended usage. For example, an individual may use instant coffee brands while in a hurry and regular ground coffee while entertaining. This "matching" between the usage requirements (benefits sought) and the product attributes (benefits provided) has major implications for marketing management/research.

Researchers have recently suggested the use of situational variables for segmentation (Abell 1980, Urban and Hauser 1980, Wind 1977). Segments may be targeted in part on their frequency of encountering various usage situations. Promotional messages may be used to link product benefits, customers, and evoked situations. Product line gaps may be identified based on situations inadequately served. The need to account for effects due to customer characteristics, product attributes, and usage situations leads to a broader perspective for market definition: *a product market is the set of products judged to be substitutes within those usage situations in which similar patterns of benefits are sought by groups of customers*. This perspective provides the basis for the "substitution-in-use" or "interchangeability-in-use" measure of inter-product/brand competitiveness advocated by several writers (Day, Shocker, and Srivastava 1979; Fennell 1978; Shocker and Srinivasan 1979; Srivastava, Leone, and Shocker 1981; Stefflre 1971, 1979; Urban and Hauser 1980). Also, because products/brands provide varying com-

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binations of benefits that are sought in different usage situations, a product/brand may compete in more than one cluster of products in a product class with multiple uses. Hence, overlapping rather than mutually exclusive clusters/markets may be relevant (Arabie, Carroll, DeSarbo, and Wind 1981).

Research applications incorporating usage situational influences have been limited in number due to lack of a general, comprehensive, and parsimonious taxonomy of usage situations that could be routinely applied. However, an analytical framework based on the work of Stefflre (1971, 1979), Belk (1974, 1975, 1979), and Day, Shocker, and Srivastava (1979) can overcome this barrier. This framework provides for the generation of product specific usage-situational taxonomies. Scenarios are generated to represent cells of the taxonomy. Then product preferences of individuals in given usage scenarios are analyzed to derive product market structures and to suggest segmentation strategies.

This paper will:

(1) examine the predictive ability of the usage-situational taxonomy (via cross-validation), since the usefulness of the entire framework is dependent on the taxonomy;

(2) illustrate that when products/services have multiple uses (are suitable for several types of usage situations), hierarchical clusters may be misleading, as they require exclusive group membership. *Overlapping* market structures are more appropriate under these circumstances; and

(3) show that interactions among situation, person, and product factors may be more *managerially* meaningful than main effects.

These objectives are achieved via an empirical application in the financial services/banking industry. The remainder of this paper is organized in four sections. The first reviews customer, product, and usage-situational effects. The second briefly describes the analytical framework and develops the usage-situational taxonomy. The third section discusses research methodology and analyses used to examine the predictive ability of the usage-situational taxonomy, and illustrates the need to use overlapping market structures when product sets with multiple uses are examined. Managerial and research issues are examined in the last section.

Implications of Situational Effects

If usage situational influences on customer preferences/choice (and hence market structures) are both statistically and substantively significant, then an understanding of the meaning of the main effects and interactions of the product, customer, and situational factors is important in drawing inferences for marketing research and management. We here emphasize the usage-situational factor and its interactions with the more traditional product and customer variables.

The meaning of various main effects and interactions and their implications are summarized in Table 1. For example, the product × usage situation interaction (row 6) will be significant if different products are seen as useful for different types of usage situations (column 2). The managerial implications include situational segmentation and the need to examine overlapping submarkets (column 3). The last column in Table 1 lists literature bases and/or rationales which provide us some direction in developing predictions about the size of relevant main effects/interactions.

While literature on usage-situational influences suggests a strong product × use interaction, especially when products/brands have multiple uses (e.g., household cleaners, clothing, snacks, financial services), it does not necessarily follow that there will be significant customer × use and customer × product × use interactions in product preferences. Miller and Ginter (1979) illustrate that the importance of attributes depends on the usage context. Consequently, controlling for the usage situation should lead to greater homogeneity in reported product preferences among respondents (Belk 1979; Hagerty 1980; Pekelman and Sen 1976; Srivastava 1980; and Srivastava, Shocker, and Day 1978). This suggests that, contrary to the hypotheses of some researchers (cf. Bass 1974) that customer preferences are inherently stochastic, it may instead be that the *situations they face* occur probabilistically, and by accounting for them, one may be able to reduce the variance of prediction errors. The greater the consistency (homogeneity) in customer preferences in given usage situations, the lower would be the expected size of customer × situation and customer × product × situation interactions.

While some predictions may be made regarding the relative size of the interactions/main effects (for example, high customer and customer × product effects when there is high variability in people's experience and/or familiarity with product classes and specific brands), each research context is likely to be idiosyncratic. Therefore, it is useful first to measure the size of these effects. Then appropriate analyses may be conducted to explore the managerial implications of the more promising effects.

Analytical Framework and Methodology

The analytical framework consists of three main stages. The first involves the generation of a product specific

TABLE 1
Meaning and Implications of Person, Product, and Situational Factors

Effect / Interaction	Meaning	Implications	Literature Base/ Observation
Customer	Customers vary in average use of products across situations.	Variation in usage rates identify characteristics of heavy/medium/light users.	Familiarity and prior usage experience with product class. Relevance of product class to segments.
Product	Products vary in average usefulness to customers across situations.	Average use of products/ brands may be interpreted as their "market share."	Product differentiation and varying marketing effectiveness of manufacturers can be expected to lead to high product main effect.
Usage situation	Variation in average usefulness of products across customers in given usage situations.	Identify situations not adequately served → identification of opportunities, product line gaps.	Low usage situation main effect in product classes that are mature and where product proliferation is evident.
Customer × product	Different (groups of) customers perceive different (sets of) products to be useful (on the average, across situations).	Segmentation feasible among customers on the basis of benefits, experience, and attitudes associated with different products/brands.	Familiarity and prior usage experience of customer segments limited to specific products/brands (perhaps, product subcategories targeted to customer segments).
Customer × situation usage	Different (groups of) customers perceive the average usefulness of the product class to be different for different (sets of) usage situations, i.e., people use the product class for different types of situations.	If the interaction accounts for a small amount of variation in preferences (as expected—see next column), small sample sizes may be adequate in research controlling for situational effects.	Response homogeneity given situational "control" suggests that person × situation interaction will explain only a small amount of variation in product preferences.
Product × usage situation	Different (sets of) products are perceived as useful (across customers) for different types of usage situations.	Situational segmentation (definition of submarkets based on usage context). Overlapping submarkets. More deterministic preference/choice models if situation taxonomy is reliable/ valid.	Dependence of product use on usage context (i.e., marketing of benefits sought/required in usage situations and benefits provided by products) likely to be important in product classes with multiple uses or "broadly defined" product sets.
Customer × product × usage situation	Different people use different products for different usage situations.	Product market definition in terms of customers, products, *and* uses.	Response homogeneity given situational control suggests *low* three-way interaction.

usage-situational taxonomy. The second deals with the collection of data in a three-dimensional matrix: preferences of *customers* and *products* in given *usage situations* (scenarios representing taxonomic cells). The third stage involves data analysis to measure the size of each main effect and interaction, followed by analyses appropriate to explicate and interpret any significant interactions that may be found. The three stages are described with the aid of an empirical example from the financial services/banking industry.

The financial services/banking market, broadly defined, is rapidly changing. While it may be obvious that checking accounts offered by different banks are likely to be substitutes, the extent to which such accounts are competitive with credit union share drafts, write-a-loan checks, or various types of credit cards is less clear, as each of these services has multiple uses, and money is inherently substitutable. Finally, because people use a variety of financial services for different purposes, the examination of substitutability between financial services based on the similarity of anticipated use is especially relevant.

Stage 1: Generation of Usage-situational Taxonomy

Belk (1979) concludes that the viability of a general taxonomy of situations is doubtful, since the situational influences that affect some behaviors (e.g., the choice of high involvement products such as automobiles) are often entirely different from those that affect other behaviors (e.g., the choice of low involvement products such as soft drinks). However, product specific usage-situational taxonomies may be easily constructed, based on the iterative procedures suggested by Stefflre (1971, 1979), Belk (1979), and Srivastava, Shocker, and Day (1978).

In the first step taken to generate our taxonomy, samples of customers were given a target product or brand (bank credit cards) and asked to suggest as many uses for that product as possible. They were then asked for other products or brands suggested by such uses and then additional uses for the expanded product list. Managerial inputs were used in adding new services (not then available in the city where the study was conducted, but available in some other cities) since the sponsoring institution was interested in their potential impact. Then an independent sample was asked to judge whether they would consider using each product for each usage situation. After a check for perceptual homogeneity, the data was aggregated across individuals to yield a summary measure of suitability: the proportion of individuals who would consider using each product for each situation. These data (average suitability measures within a products-by-uses matrix) were then factor analyzed by the method of principal components with usage situations as variables. Situations and products can be plotted in reduced space based on their loadings and scores, respectively, on the principal components. The dimensions of this reduced space are interpreted to understand why situations cluster as they do, in that they have similar patterns of products considered suitable. This understanding is used to form a tentative situational taxonomy. Details of procedures for generating the taxonomies may be found in Belk (1979), and Srivastava, Shocker, and Day (1978).

The procedure, when implemented in the financial services market, resulted in three major situational dimensions: the dollar amount required for payment (subsequent analysis revealed three ranges as relevant: \$50–399, \$400–999, \$1,000–2,000); location (local versus out of town); and retail credit availability (was the purchase being made in an establishment offering purchase credit?), hereinafter referred to as "retail credit setting."

Stage 2: Generation of Customer × Product × Usage Situation Matrix

The next step was to develop scenarios to represent taxonomic cells of the usage-situational taxonomy. This is usually a simple task if there are only two or three taxonomic dimensions, each with a limited number of levels. The three major dimensions of the taxonomy lead to (3 × 2 × 2 =)12 combinations (taxonomic cells) that would be necessary to estimate the main effects and all possible interactions. Two equivalent sets of scenarios (12 in each set, 24 total) were constructed in order to cross-validate the taxonomy. For example, a taxonomic cell which (1) involved a low dollar amount, (2) required an out-of-town setting, and (3) where retail credit was not available, was expressed by the scenario: "While you are out of town on a trip you have some unexpected problems with your car. The repair bill, at a small independent garage, is about \$100 and must be paid immediately." An equivalent scenario in the second set would have been generated using the same type of information in a different "generic" setting (for example, dinner as opposed to automobile repair). The advantage of this procedure over using ad hoc descriptions is that all usage situations are portrayed by an equal number of informational elements and can readily be represented by dummy variable codings.

The primary data collection task required respondents to judge the appropriateness of each of 24 services (brief descriptions provided in Table 3) for each of 12 usage situational scenarios on a four-point likelihood of use scale (1 = not at all likely, service totally inappropriate for use; 2 = somewhat likely; 3 = quite likely; 4 = extremely likely (would definitely use)).

The managerially relevant audience (for the target service, bank credit cards) corresponded to higher socioeconomic groups. An upscale subsample was selected from a panel listing in Pittsburgh during May 1978. Demographic data were available from the panel listing. In addition, data were collected on attitudes towards savings and credit usage, along with a condensed version of Rotter's interpersonal exploitation scale (see Chan and Campbell 1974 for details).

Four hundred questionnaires were mailed, of which 260 were returned after two follow-up calls. Two hundred and thirty (115 for each situational set) were usable. There were no significant differences (at the $\alpha = 0.10$ level, or better) between respondents and nonrespondents in terms of demographics such as income, education, age, occupation of the household head, family size, and the number of savings and checking accounts.

The data collected represent two respondent × product × situation matrices of size (115 × 24 × 12). The third stage, estimation of the relative importance of main and interaction effects followed by analyses appropriate to explicate and interpret the more sizeable effects, is described next.

Analyses and Results

Relative Contributions to Variance

The relative importance of main/interaction effects may be assessed via a three-way mixed effects analysis of variance model.[1] The results (estimates of mean square, percent contributions) for both situational sets are presented in Table 2. As is readily observed, the results for the two balanced situational sets are strikingly similar. In both cases the relative contribution to variance of preference (likelihood of use) due to the main effect of situations and the situation × customer interaction terms are minimal. The major contributions to explained variance are due to person and product main effects and the persons × product and product × usage situation interactions (about 13, 13, 19, and 16%, respectively).

The person and product main effects provided general information. The findings represented aspects about the market that were reasonable (some products, e.g., credit cards and checking accounts, were seen as more useful than others, and some persons, those shown via regression analysis to have higher education and greater mobility, were heavier users of financial services than others). The more insightful effects were clearly the product × usage situation interaction (under what circumstances are different services used more often?) and the person × product interaction (what types of people are likely to use different patterns of services?), which were beneficial from the viewpoint of segmentation based on situations and customers.

Examination of Customer × Product Interaction Effects

An attempt was made to provide some explanation for the significant person × product interaction through the use of canonical analysis. Individuals' characteristics were used as predictor variables and the average (across all situations) likelihood of use for the 24 financial services as the criterion variables. The predictor variables that were used included customer demographics (sex, age, household income, occupation, number of incomes per household, education, and family size), "enriched" demographics (length of residence and home ownership), and attitudes relevant to financial services (fear of interpersonal exploitation, convenience credit usage, and advocacy of savings).

The canonical analysis demonstrated that these

[1]The expected mean squares relationships for a three-way mixed effects model (with situations and products as fixed factors and individuals as random) are presented in Table 2. Corresponding solutions for estimates of variance components are derived from the expected mean square formulae (see Peng 1966, chapter 5). Since there is only one observation per cell, the error variance is confounded with σ_{IJK}^2, as no independent estimate of the three-way interaction is available. Accordingly, it is necessary to assume that either the error variance or the three-way interaction term is zero in order to estimate the relative contributions to variance (Endler 1966, Peng 1966).

TABLE 2
Relative Contributions to Variance in Product Appropriateness[a]

Source	D.F.	Expected Mean Square[b]	Set One: Estimate of MSQ[c]	Set One: Percent Cont.	Set Two: Estimate of MSQ[c]	Set Two: Percent Cont.	Average Percent Cont.	
Persons (I)	114	$\sigma_E^2 + KM\sigma_I^2$	42.40	12.55	41.06	12.74	12.65	←
Situations (J)	11	$\sigma_E^2 + NM\sigma_J^2 + M\sigma_{IJ}^2$	16.44	0.43	18.39	0.55	0.49	
Products (K)	23	$\sigma_E^2 + NK\sigma_K^2 + K\sigma_{IK}^2$	242.07	14.46	202.28	11.37	12.92	←
Persons × Sit. (IJ)	1,254	$\sigma_E^2 + M\sigma_{IJ}^2$	0.89	2.91	0.78	2.67	2.79	
Persons × Prod. (IK)	2,622	$\sigma_E^2 + \sigma_{IK}^2$	2.60	17.73	2.85	20.38	19.05	←
Sit. × Prod. (JK)	253	$\sigma_E^2 + \sigma_{IJK}^2 + N\sigma_{JK}^2$	25.16	16.53	22.04	15.18	15.86	←
Error + (IJK)	28,842	$\sigma_E^2 + \sigma_{IJK}^2$	0.52	35.39	0.47	37.11	36.24	
Total	33,119			100.00		100.00	100.00	

[a]Three-way mixed effects model (subjects random: products and situations fixed) where E = error, N = number of subjects, K = number of situations, M = number of products, R = residual.
[b]See Peng (1966), chapter 5.
[c]Estimate of mean square obtained by adjusting for confounded error variance.

customer characteristics were significantly related to the relative use of financial services. The "explained" variation (technically called "redundancy") in mean service usage, given demographic, enriched demographic, and attitudinal data was a modest 7.85% (significant at $\alpha \leq .01$). Nevertheless, some insight into the relevance of person × product interaction may be gained by viewing the patterns of correlations among predictor and criterion variables and the significant canonical variables (Table 3).[2] For brevity we will discuss only the first two canonical relationships.

The first relationship was associated with individuals who were (relative to the sample) young, wealthy, mobile (were low in terms of length of residence in present location), professional, educated, low in fear of interpersonal exploitation, high in belief in using credit as convenience, and low in advocating savings. The related service usages were chiefly associated with credit card use: cash advance from bank card, overdraft protection (bank cards used to cover checks drawn on insufficient funds), bank credit cards, and travel and entertainment cards. Given this pattern, there was also a relatively low use of cash withdrawn from checking accounts. Persons who might be described as upscale but young seem to be likely to become heavy users of credit cards (and were also positively associated with adoption of newer services such as NOWs and overdraft protection).

The second relationship shows a contrasting pattern overall. Even though some variables are common with the first relationship, the gestalt of the profiles is changed. The service use pattern was associated with low (relative to the sample) use of almost all installment loans involving interest payments, and a low intended use of cash and cash withdrawn from savings accounts. Individual variables associated with this pattern were relatively high income, education, and occupation, as before. However, this relationship was also correlated with individuals who were relatively older (as opposed to the former's youth), and a positive association with advocacy of savings (vs. the former's negative). This pattern may explain the apparent aversion to financial services involving interest payments among persons with similar income, education, and professional status.

Reversing the signs of the loadings may give additional insight into patterns among the sets of variables. For example, the second relationship could also be viewed as one involving heavy usage of interest payment loans among persons in the sample who were relatively young, nonwealthy, nonprofessional, less educated, and nonadvocates for savings. Keeping in mind that the range of people in this sample made all respondents relatively good credit risks, this reversal of signs could provide an interpretation useful in targeting bank credit cards to such persons by developing advertising messages which emphasize the flexibility that bank cards provide for loan repayment (relative to installment loans).

One might identify persons likely to be good and bad prospects for varying sets of services based on the characteristics of individuals and their proclivity to use different types of services (across all usage situations). However, the influence of situational factors in this study suggests combining this analysis with other findings to provide further insight regarding the market structure. This follows.

Examination of Product × Usage Situation Interaction Effect

By aggregating data across individuals, it is easy to develop a measure of the relative likelihood of use of each service in each usage situation. Interproduct distances or similarities may then be computed (across situations), and a variety of data reduction techniques such as cluster analysis, factor analysis, and multidimensional scaling could be used to examine the market structure. However, situational influences are not useful if they are idiosyncratic. If market structures based on substitution-in-use were to be managerially relevant, it was important to check whether the usage-situational taxonomy was useful in *consistently* predicting the products that were likely to be used. Then market structures could be developed based on products seen as appropriate for (subsets of) usage situations.

Predictive Ability of the Taxonomy

Since the two situational sets were administered to different samples, a reasonably strong test of predictive ability would be cross-validation between the two samples. This is done by examining whether the regression coefficients corresponding to the two situation sets were similar and the extent to which coefficients based on one set could predict product usage in the other.

After a test of perceptual homogeneity within each sample, responses were aggregated across individuals to arrive at two (one for each situational set/sample) product × usage situation matrices of size (24 × 12). The cells (A_{jk}) of these matrices have entries equal to the average likelihood-of-use of service k in situation j. This stated likelihood of use for each service in given situations was estimated by regressing against dummy variable situational codings for retail and nonlocal (0

[2]In interpreting canonical analysis, one conventionally looks at variables with high loadings on each canonical root (expressed as correlations between the variables and the optimally weighted linear combinations), although other heuristics may be used (Alpert and Peterson 1972; Wildt, Lambert, and Durand 1982). This discussion will note variables whose loadings were above .28 (meaning about 8% shared variance between the variable and the canonical root).

TABLE 3
Canonical Analysis of Financial Service Usage and Person Variables

Variables	Canonical Loadings[a] I	II	III
	Predictor Set		
Sex (1 = F, 2 = M)	.204	−.108	.225
Age (1–5, 5 highest)	−.461	.331	.464
Household income (1–8, 8 highest)	.366	.507	−.152
Length of residence (1–4, 4 longest)	−.427	−.252	−.074
Home ownership (0 = rent, 1 = own)	.203	.217	.295
Occupation (0 = other, 1 = professional)	.533	.452	−.272
Number of incomes (1 = single, 2 = double)	−.134	−.041	.033
Family size (1–7)	−.232	.210	−.221
Education (1–7, 7 highest)	.643	.312	.129
Interpersonal exploitation (fear)	−.302	−.169	−.233
Convenience credit user	.386	−.148	.269
Advocate for savings	−.320	.279	−.009
	Criterion Set		
Cash	−.232	−.329	−.407
Checking (cash)	−.294	.067	−.392
Checking (check)	−.118	.231	−.163
Debit card	−.012	−.160	.144
Savings (cash)	−.207	−.298	−.449
Savings (check)	−.064	−.045	−.334
NOW (check)	.264	.249	−.144
NOW (card)	.228	−.045	−.217
Savings certificate	−.028	−.116	−.225
Stocks and bonds	−.046	−.140	−.297
Borrow against savings	.213	−.129	−.214
Traveller's check	.113	−.061	−.335
Cash advance—bank card	.424	−.073	−.066
Overdraft—checking	.521	.055	−.041
Check credit	.364	.069	−.097
Bank credit card	.460	.025	.047
T&E credit card	.279	−.209	−.078
Retail credit card	.215	−.425	−.160
Personal loan	.013	−.260	−.319
Bank installment loan	.001	−.400	.136
Finance co. installment loan	.078	−.281	.021
Credit union installment loan	−.089	−.330	.051
Retail installment loan	.069	−.495	.094
Revolving credit loan	.153	.125	.070
Redundancy C/P	.019	.015	.012
Percent of total redundancy (= .0785)	24.200	18.980	15.290
Roots	.338	.272	.229
Canonical R	.582	.522	.479
Chi-square	86.900	66.860	54.870
Degrees of freedom	35	33	331
Significance of R	<.005	<.005	<.005

[a]Critical loading = 0.28 (meaning about 8% shared variance between the variable and the linear combination used in the significant canonical root), i.e., loadings > 0.28 are significantly > 0.00.

if nonretail or local, 1 otherwise) and the dollar amount required as predictors. Based on the models comparison approach, a simple pooling test was conducted to examine whether the regression coefficients for the two samples were significantly different.

As noted in the last column of Table 4, the parameter estimates were significantly different (at α = .10 or better) for the two samples except in the case of only two of twenty-four services (stocks and bonds, and cash advance on a bank credit card). This may be expected by chance alone (2/24 = 0.083). The average adjusted R-square (across services) for the pooled regression equations was 0.695. The interpretations based on the regression coefficients were intuitive. For example, in both situation sets, bank credit cards were more likely to be used (1) in retail credit (as opposed

TABLE 4
Regression Equation for Products[a]

Product	Retail	Not Local	$ Amount	R-square	Signif.[b]
Cash	−.026	.154	−.797	.68	.91
Checking (cash)	−.222	−.454	−.763	.68	.38
Checking (check)	−.186	−.058	−.940	.84	.61
Debit card	.566	.336	−.341	.63	.41
Savings (cash)	−.288	−.841	.191	.86	.47
Savings (check)	−.399	−.756	.247	.85	.94
NOW (check)	−.548	−.119	.022	.31	.96
NOW (card)	−.144	−.909	−.060	.82	.56
Savings certificate	−.336	−.445	.495	.66	.43
Stocks and bonds	−.395	−.334	.506	.63	.08 ←
Borrow against savings	−.272	−.427	.612	.75	.79
Traveller's check	.044	.856	−.274	.87	.78
Cash advance–bank card	−.251	.604	−.298	.55	.99
Overdraft–checking	−.435	.458	−.026	.42	.04 ←
Check credit	.425	.760	.125	.70	.54
Bank credit card	.799	.238	−.177	.77	.76
T&E credit card	.075	.451	−.287	.33	.36
Retail credit card	.934	−.112	−.067	.92	.44
Personal loan	−.590	−.075	.165	.42	.28
Bank installment loan	−.014	−.243	.849	.83	.73
Finance co. installment loan	.095	−.188	.855	.79	.72
Credit union installment loan	−.117	−.492	.666	.80	.31
Retail installment loan	.823	−.154	.374	.75	.98
Revolving credit loan	.127	−.288	.833	.90	.33

[a]Pooled (across the two situational sets), standardized regression coefficients.
[b]Probability that regression coefficients estimated from the two situational sets are not different.

to nonretail) settings, (2) while out of town, and (3) for the lower dollar range.

The regression equations for services obtained from situational set 1 were used to predict the likelihood of use of services in situational set 2, and vice versa. These predictions were compared to the stated likelihood of use. Additionally, the stated likelihood of use was also compared with "naive" predictions, that is, the average (across situations) likelihood of use for services. If the usage-situational taxonomy was *not* useful in accounting for variation in likelihood of use of services, then the naive predictions should perform as well. For each set of situations, predictions (based on parameters derived from the other set) of the likelihood of use of products were highly correlated with stated values (average correlation across all 24 situations = 0.948). The naive predictions when related to reported values resulted in an average correlation of 0.678. The difference (.948 − .678 = 0.270) represents the improvement of predictive ability due to the taxonomy, and is therefore a measure of the usefulness of the taxonomy. The usage-situational taxonomy was most beneficial for predicting reported usage in situations for which there were a limited number of suitable product offerings (for example, for out-of-town situations requiring larger dollar amounts). This may be expected, as naive predictions of market share are not likely to perform as well as situationally determined predictions when deviations from the average usage are substantial.

Product Market Structures

The significant products by situations interaction and the high predictive ability of the usage-situational taxonomy confirm the dependence of the likelihood of use of products on the situation. This dependence underscores the need to examine overlapping product-markets, as products can potentially be competitive in more than one (situationally defined) submarket. We examine both hierarchical and overlapping clusters, in order to illustrate salient differences and attendant implications.

Figure 1 summarizes the results of hierarchical clustering of products based on the similarity in their use across situations. The more similar pairs of products thus had higher correlations in the perceived likelihood of use across varying situations.[3] In the tree

[3]If a researcher is interested in examining *potential substitution* (as opposed to *current* level of usage) between products across situations (as was the case in this study), then only the co-variability of likelihood of use across situations as reflected by the interproduct correlations is pertinent. If, however, the interest lies in current levels of usage, it would be pertinent to compute interproduct distances (dissimilarities) based on unstandardized measures of suitability (likelihood) for use of products in varying situations.

FIGURE 1
Hierarchical Clustering of Financial Services

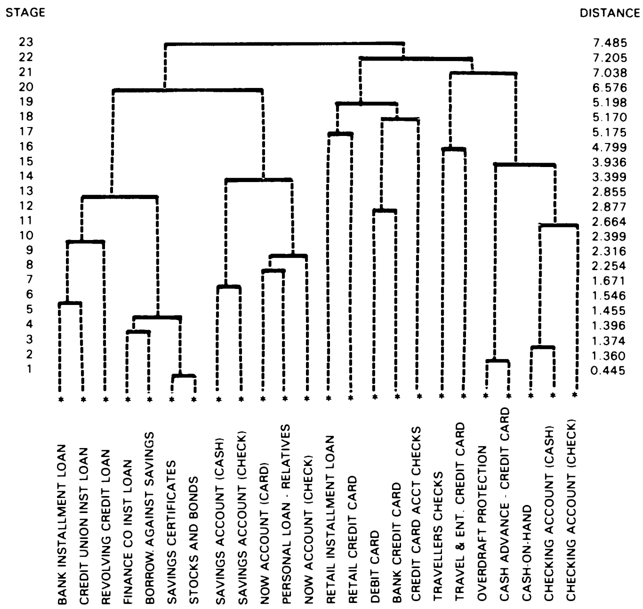


diagram in Figure 1, products that were most similar were grouped first (savings certificates and stocks and bonds). In the next stage, the next most similar pair was grouped, and so on. As the grouping process proceeds, the dissimilarity of sets of products grouped at the latest stage increases. Based on the traditional heuristics for cluster analysis, five clusters appeared to be the most meaningful grouping.

Interpretation of competitive market structures appears to be relatively straightforward. For example, based on their similarity in perceived appropriateness across a variety of situations, travel and entertainment (T&E) credit cards are seen as primarily competitive with traveller's checks. In addition, retail installment loans were in an entirely different cluster compared to bank, credit union, and finance company installment loans, implying limited competition between the first and the latter three.

However, the presence of a strong situations by products interaction suggests that some products may belong in different clusters, depending on the situation (where they may compete with different sets of competitors). An appropriate modification in methodology for use in analyzing data in such circumstances would be overlapping cluster analysis.

Overlapping clusters were obtained by using the SAS version of the ADCLUS (see SAS Institute 1981 for details). The ADCLUS (for ADditive CLUStering) model was developed by Shepherd and Arabie (1979). Arabie, Carroll, DeSarbo, and Wind (1981) provide a good discussion of the model. Since details of the SAS version of the ADCLUS program are available elsewhere, we provide only a brief description.

The advantage of ADCLUS over hierarchical clustering algorithms is that products can belong to one or more clusters. If product A is competitive with products K, L, and M as well as with X, Y, and Z (which are quite different from K, L, and M), then it can be placed in both groups. Hierarchical clusters require exclusive group memberships. Therefore, A would have been "forced" to cluster with only one of the two groups, leading to the potential loss of insightful information.

The ADCLUS model may be viewed as a discrete version of multidimensional scaling (MDS) with the clusters in ADCLUS corresponding to the dimensions in MDS. ADCLUS can be viewed as allowing locations of either 1 (presence in cluster) or 0 (absence from cluster) along each dimension. Therefore, two products (A, B) which belong to the same two clusters would be more similar compared to another two products (A, C) which have common membership in only one cluster. However, since the clusters are allowed to have varying importances, each cluster contributes different amounts toward implied similarities.[4]

Both cluster weights and cluster membership are simultaneously estimated via iterative fitting techniques which minimize the variance between the actual and predicted similarities. The SAS version of ADCLUS uses an approach similar to stepwise regression to derive clusters. The first cluster is developed to explain as much of the variance in pairwise similarities as possible. Then the second cluster is developed to maximally explain the residual similarities, and so on. Thus the R-square (or proportion of variation in similarities explained by the model) can be sequentially improved by increasing the number of allowable clusters.[5]

[4]In other words, the similarity between two products i and j (S_{ij}) can be written as:

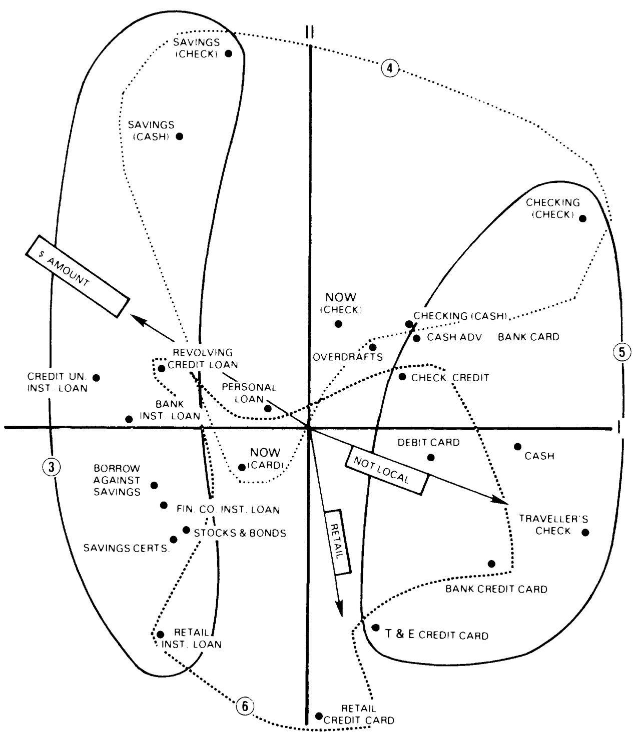
$$S_{ij} = \sum_{k=1}^{m} w_k \cdot x_{ijk} + e_{ij}$$

where

e_{ij} = error in similarity (not explained by model);
$x_{ijk} = \begin{cases} 1, \text{ if both i and j belong to cluster k,} \\ 0, \text{ otherwise;} \end{cases}$
w_k = a nonnegative weight representing the importance of cluster k in describing similarities among products.

[5]Although one can examine the increase in R-square in a manner similar to stepwise regression to determine whether p cluster solution is "significantly" better than a p-1 cluster solution, the procedure is not recommended because there is no generally acceptable model for distribution of error terms of similarities. Further, the iterative clustering procedure is conditional on previous groupings, just as predictor variable selection in stepwise regression is dependent on variables already entered.

FIGURE 2
Financial Services Market Structure (Overlapping Clusters)



The SAS version of ADCLUS was used to cluster products based on the similarity in the appropriateness for use of products across situations (used earlier with the hierarchical approach). The 1, 2, 3, 4, 5, 6, 7, and 8-cluster solution explained 41.2, 63.5, 70.0, 74.1, 78.2, 81.4, 83.1, and 83.9% of the variance in similarities (interproduct correlations), respectively. However, as in the case of MDS, there is a trade-off between the goodness of fit and interpretability and parsimony. Starting with the seventh cluster, the groupings became less interpretable. Also, there was very little gain in explained variance starting with the seventh cluster. Accordingly, six clusters were retained. The six-cluster solution is presented in both pictorial (Figure 2) and tabular (Table 5) formats.

In order to facilitate interpretation, selected clusters (3 to 6) are enclosed by contours on a multidimensional representation of products in Figure 2. This was obtained by means of principal components analysis of the products by uses matrix, with products as "cases" and situations as "variables." Factor scores represent the degree to which products were seen as suitable for those situations that were highly correlated with that factor. Situations which load on the same factor have in common the fact that products seen as useful in one situation would also be seen as useful in the others. Factors can also be interpreted *objectively* by examining the correlations between the factor loadings for each factor and the taxonomic descriptors (dummy variables) across situations. Factor 1 was positively correlated with "not local" and negatively related to "dollar amount." Factor 2 was negatively related to "retail." In light of these interpretations, the product positions appear reasonable. For example, bank credit cards are more likely to be used in out-of-town retail settings where low/medium amounts are required.[6]

Each cluster and its interpretation are provided in Table 5. These interpretations were made by comparing the average likelihood of use of products in each cluster for various types of situations. The reader may examine the regression coefficients in Table 4 or product positions in Figure 2 in order to develop an understanding of the similarity of usage of products within clusters. The first cluster consisted of products that were seen to be more useful when large amounts of money were required for use in town and cluster 2 when smaller (low to medium) amounts were required in retail settings. Retail installment loans were "unexpectedly" grouped with products that were deemed as more useful for situations requiring medium ($400–999) dollar amounts, rather than with other installment loans as anticipated by managers. The implications of this finding are discussed later. Cluster 3 consisted of products more likely to be used in in-town retail settings requiring larger amounts of money. This cluster, with the exception of retail installment loan, is a subset of cluster 1. Cluster 4 consists of products more likely to be used in in-town nonretail settings when low/medium amounts are required. Thus the cash and check modes for accessing savings accounts were seen as useful for both low/medium amount, nonretail settings as well as for high dollar situations. Cluster 5 consists of products more likely to be used in out-of-town settings where low/medium amounts were required. Finally, cluster 6 consists of products more likely to be used in retail settings while out-of-town for low/medium amounts.

Each cluster may be viewed as a submarket. Thus bank credit cards, credit card account checks, and debit cards are competitive with retail credit cards and retail installment loans in out-of-town retail settings, and with travel and entertainment credit cards and traveller's checks in out-of-town nonretail settings. Travel and entertainment cards are viewed as less suitable (compared to bank cards) in out-of-town retail settings due to lower retailer acceptance. Credit card account checks (e.g., "Masterchecks") are viewed as

[6]Three factors representing 90.8% of the variance were obtained. However, factor scores (for the products/cases) on only the first two components (accounting for 74.4% of the variance) are plotted. Consequently, some contours may seem "awkward" since the third component of the factor solution is not shown.

TABLE 5
ADCLUS Groupings for 24 Financial Services

Order of Entry ⇒	1	2	3	4	5	6
Rank by Weight ⇒	**1**	**4**	**2**	**5**	**3**	**6**
Cluster Weight ⇒	**64**	**43**	**56**	**35**	**50**	**31**
Cash on hand		X			X	
Checking (cash)		X		X		
Checking (check)		X		X	X	
Debit card		X			X	X
Savings (cash)	X		X	X		
Savings (check)	X		X	X		
NOW account (check)	X			X		
NOW account (cash card)	X			X		X
Savings certificate	X		X			
Stocks and bonds	X		X			
Borrow against savings	X		X			
Traveller's check		X			X	
Cash advance–bank card		X		X	X	
Overdraft–checking		X		X		
Check credit–bank card		X			X	X
Bank credit card		X			X	X
T&E credit card		X			X	
Retail credit card		X				X
Personal loan–relative	X			X		
Bank installment loan	X		X			
Finance co. installment loan	X		X			
Credit union installment loan	X		X			
Retail installment loan		X	X			X
Revolving credit loan	X		X			X

Interpretation of Clusters (in order of entry)

(1) Products likely to be used when large amounts are required (local use).
(2) Products likely to be used when low/medium amounts are required in retail settings.
(3) Products likely to be used when large amounts are required in retail settings (local use).
(4) Products likely to be used when low/medium amounts are required in nonretail settings (local use).
(5) Products likely to be used when low/medium amounts are required in out-of-town settings.
(6) Products likely to be used when medium amounts are required in retail settings while out of town.

more acceptable in out-of-town settings compared to overdraft protection (in a checking account).

The main advantage of the ADCLUS procedure, its ability to embed a product in several clusters or submarkets, is demonstrated by comparing it with traditional, nonoverlapping (hierarchical) methods. While the hierarchical and overlapping clustering solutions would have been identical if only two clusters were derived in each, this high level of aggregation would not be very useful managerially. If the interest lies in examining groups of products that compete more directly, then the hierarchical solution can be misleading. For example:

(1) In the hierarchical clustering solution (Figure 1), retail installment loans were in an entirely different branch compared to bank, credit union, and finance company installment loans and revolving credit loans. In the overlapping clustering solution (Figure 2), retail installment loans were grouped competitively with the above loans when larger amounts of money were required (cluster 3) and with bank and retail credit cards, and debit and NOW account cards, revolving credit loans, and credit card account checks when smaller (medium amount) sums were required (cluster 6). Cluster 6 from the overlapping solution is quite informative. It suggests that banks can strengthen their positions in the medium dollar retail submarket where bank installment loans are not competitive via the check credit route or the debit card route. In addition to services in cluster 6, one possibility is the development and active promotion of write your own loan programs, based on simple interest, for customers with preapproved credit lines. Another prospect is the active advertising/promotion of bank credit and debit cards for in-town retail use. The latter strategy has a side benefit in that it would lead to a reduction of the number of checks written, thereby lowering processing costs (since card billings are cheaper to process, and retailers pay a fee for the services provided by banks).

(2) In the hierarchical solution, travel and entertainment credit cards were viewed as primarily competitive with traveller's checks, and to a lesser extent with clusters 3 and 5 products (in Figure 2). However, in the overlapping solution, travel and entertainment credit cards were competitive with bank credit and debit cards for out-of-town nonretail situations (cluster 5, Table 5) and not quite competitive in out-of-town retail situations, probably due to lower retailer acceptance (cluster 6, Table 5). Obviously, the hierar-

chical clustering solution would be misleading in implying lack of competition between bank and travel and entertainment cards. The overlapping solution suggests that competition between them is very real for out-of-town nonretail settings and could potentially increase in the retail settings if the T&E credit card companies were to concentrate on obtaining increased retailer coverage.

(3) In the overlapping clustering solution (Figure 2), NOW accounts (cards) are viewed as competitive with checking and savings accounts for in-town nonretail situations requiring low dollar amounts (cluster 4, Table 5) and with bank debit and credit cards for in-town retail situations requiring low dollar amounts (cluster 6, Table 5). The hierarchical structure would have classified NOW accounts (card) as primarily competitive with savings accounts, personal loans, and NOW accounts (check). The implication of the overlapping structure in the case of NOW accounts (card) is that the product can be promoted for use in retail settings by banks (along with debit cards and credit card account checks) to strengthen their position in the retail market. If nonoverlapping clustering is used for analysis, this differential market structure would not be found.

Research and Managerial Implications

This paper has presented a framework for market structure analysis that is likely to be useful if the research interest lies in examining competition among product variants/categories (as opposed to among brand of a narrowly defined product category), especially when the set of alternatives being examined has multiple uses. In such research contexts, the usage situation can be expected to influence the preference for, and the likelihood of use of, products by customers. The analytical framework calls for the development of a product specific usage-situational taxonomy and the subsequent collection of data in a three-dimensional matrix format: perceived likelihood of use (and/or other measures of preference/appropriateness) of *products* in given *usage-situational scenarios* (corresponding to taxonomic cells) by different *customers*. This data can be subsequently analyzed to determine the size and the meaning (interpretations) of the various main and interaction effects.

The analytical framework, when implemented in the market for banking/financial services (which are inherently appropriate for multiple uses) led to a relatively simple usage-situational taxonomy. Cross-validation between two different sets of usage situations (each administered to a separate sample of customers) clearly established the usefulness of situational variables in improving predictive ability of consumer choice/preference models and the robustness of the product specific usage-situational taxonomies. The high predictive ability of the usage of the usage-situational taxonomy, coupled with the fairly minimal customer × usage situation interaction, suggests a high degree of response homogeneity (across customers), given situational control. As discussed by Belk (1979) and Srivastava (1980), this response homogeneity implies that smaller samples would be adequate in research studies that control for the effects of the usage situation (relative to comparable studies that do not).

This study clearly illustrates that the importance of usage-situational influences cannot generally be inferred from the main effect of situations (which in this case accounted for only a small part of the variation in the likelihood of use of products by individuals). As long as approximately the same number of products are perceived to be useful in each situation, the main effect of situations may not be significant. However, if the usage context influences preference/choice, the various products will be relatively more or less likely to be used depending on the benefits sought in situations. Hence, it is the interaction of products and usage situations that would be expected to be indicative of the situational influence on choices among a product or service set.

While hierarchical market structures may be developed based on measures of substitution-in-use, these structures may be misleading because products can be assigned to one and only one branch of a tree (each branch may be viewed as a submarket). This exclusivity requirement is incompatible with the basic reason for examining usage-situational influences. When products (within a set being examined) have multiple uses, each product may be competitive with different subsets of products, depending on the use (usage situation). Accordingly, overlapping clusters become more relevant. As illustrated in the previous section, the discrepancies between hierarchical and overlapping structures were salient in that the latter offered managerial insights—with attendant potential actions—which would not have been apparent otherwise.

An understanding of interactions between products and situations can also be very useful for addressing strategic marketing concerns such as the identification of opportunity gaps between product variants. Opportunities can be identified by examining situations inadequately served by current product offerings. For example, few of the 24 products evaluated by respondents were judged very suitable for use in out-of-town settings requiring large amounts of money. While these situations do not arise very frequently for the average bank customer, they do occur relatively more often for upscale customers who are also more credit worthy. Customers frequently encountering out-of-town situations may be identified by examining the frequency of out-of-town purchases in credit card histories (copies of billings) or other such archival data. The importance of this segment may also be indexed by the volume of such purchases, and this group of customers may be targeted for special marketing efforts. Banks may develop a differential advantage over competing banks by instituting and promoting mechanisms that allow these upscale customers to use services in such usage contexts. These customers may be provided with a high credit limit and encouraged to use bank credit cards and credit card account checks. Alternatively, banks can now offer money market funds with check privileges. These may fit customer needs for liquidity, portability, and high yield.

The presence of multiple offerings within a cluster suggests the duplication of efforts in that submarket. For example, several banking services (checking, savings and NOW accounts, overdraft checking, cash advances on bank cards) are in cluster 4 of the overlapping solution. As interpreted earlier (see Table 5), cluster 4 represents products seen as relevant for local, nonretail, low/medium dollar situations (incidentally, the most frequently encountered type of situation). Separate advertising/promotion of these services is likely to result in cannibalization. They might, therfore, be promoted as a package.

It is important to remember that the substitution-in-use measure and overlapping clustering approaches are likely to be useful for addressing strategic issues when management is concerned with current as well as potential competition among a broadly defined set of products. However, for tactical considerations, when the managerial interest lies within a narrowly defined product category where usage-situational effects are likely to be minimal, hierarchical clustering procedures would be more relevant (Urban 1981).

In summary, the major implications of the research presented in this paper include: when usage-situational influences are controlled for, the predictive ability of choice/preference models can be improved; the interactions among situations and products are more meaningful than situational main effects; person × product interactions may also yield benefits augmenting what is shown in either main effect; and hierarchical clusters may be misleading when examining competition at the product category/variant (as opposed to the brand) levels when usage-situational influences are likely to be important, and overlapping clusters may then be more desirable. Advances in the concepts and analytical methods shown here may lead to substantial benefits to the firms that utilize them in their research and strategic planning.

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