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Publication of this paper sponsored by Committee on Traveler Behavior and Values.

Life-Style Segmentation in Travel-Demand Analysis

ILAN SALOMON AND MOSHE BEN-AKIVA

Market segmentation, when used as a method for accounting for cross-sectional taste differences, is often applied in travel-demand analyses. This paper suggests the employment of the life-style concept as an improved basis for segmentation. Life-style is defined as the behavioral pattern that results from three major life decisions: the decision to form a household, the decision to participate in the labor force, and the orientation toward leisure. By using available socioeconomic variables, an attempt is made to identify life-style groups and to use them as market segments in a joint mode and destination choice model. Two tests are presented. One is the use of life-style-specific variables in the model specification and the other is the estimation of separate models for each market segment. Both approaches have shown an improvement in the model performance compared with either a pooled model or an income-based and a life-cycle/occupation-based segmentation. Further refinement of the ability to identify life-styles is suggested.

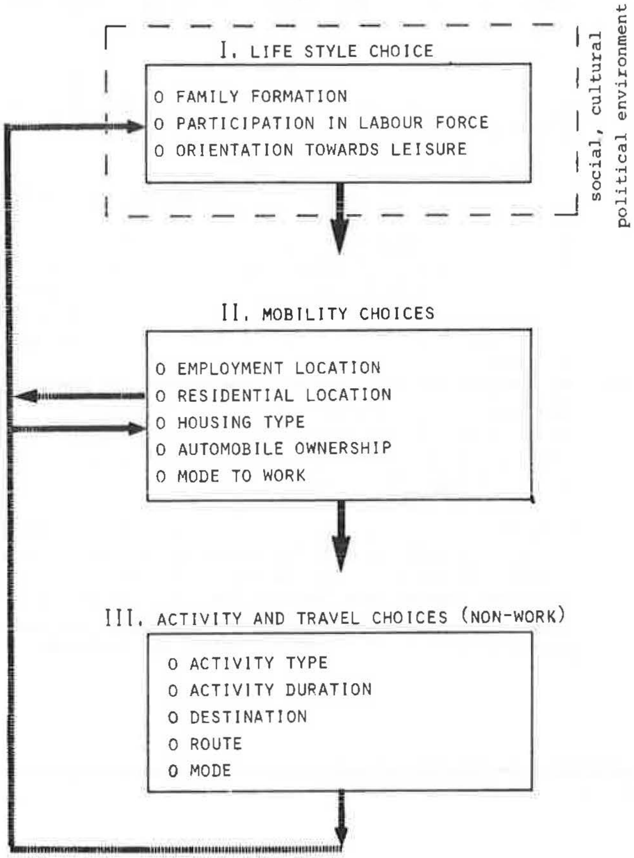
The shifting focus of travel-demand analysis to individual or household behavior has drawn attention to the problem of cross-sectional differences in individuals' tastes. A number of pragmatic solutions have been used over the past few years to account for taste differences. Generally, the approach entails the use of market segmentation, which creates some homogeneous groups that are likely to behave in a similar manner under changing conditions. Yet it seems that in many of these efforts there is a lack of a theoretical basis.

This paper presents an attempt to use a segmentation that is based on the concept of lifestyle. Life-style segmentation, as defined in this paper, offers a theoretical basis for differentiating between behavioral groups. It is integrated in the framework of the choice hierarchy that distinguishes between short- and long-run decisions in travel behavior. Although there still exists a serious gap between the conceptual definition of life-style and its empirical definition, an attempt to apply the concept is presented.

The concept of life-style is widely used in market research as a basis for segmentation (1,2). It is also regaining ground among sociologists who suggest that life-style differentiating among groups has greater behavioral relevance than differentiation along social or economic classes (3,4).

A segmentation based on life-style is compared with alternative market-segmentation schemes based on socioeconomic characteristics. The performance of a mode and destination choice model for shopping trips is used to evaluate the alternative schemes. The results of this analysis indicate that life-style segmentation is an improved approach compared with the others tested in this research.

Figure 1. Extended choice hierarchy.



GENERAL

Market Segmentation in Travel Behavior

The widely used method for accounting for systematic taste variations is the segmentation of the population into groups that are assumed to be homogeneous with respect to the behavioral aspect under study. The choice of variables to be used as a basis for segmentation depends mainly on their power in improving the performance of a well-specified model in the specific context it is to be used. Most importantly, the behavioral relevance of the segmentation basis needs to be considered. Segmentation along an irrelevant dimension will result in inaccurate prediction results. Only variables for which there are sound theoretical grounds for their explanatory power of a particular choice situation can be used successfully. The variable used must also have a limited number of distinct values that are relevant to the behavior under study, so as to generate a manageable number of segments.

The variety of experimentations with market segmentation carried out to date can be classified along three dimensions: the nature of the variable used, its mathematical form, and the applicability of the segmentation to varying situations. Most often, demographic and socioeconomic variables as well as choice constraints are used as a basis for segmentation. The first type includes attributes such as age, income, etc. (5-7). The second type differentiates between groups that face different constraints (or lack of them) such as modal availability (5,8). The third type of variable used is attitudinal or perceptual data (9).

The second dimension is the form in which the variables are used. The segmentation can be based on the values of the variables directly, either in a unidimensional or multidimensional form, or, alternatively, the variables may be transformed into a composite variable that serves as the basis for segmentation. An example of the first type is given by Ben-Akiva and Lerman (7), who have used a simple combination of life cycle and occupation. The second type was used by Golob and Burns (8), Dobson and Tischer (9), and Tardiff (10), who have used composite variables like principal components.

The third dimension is a conceptual one; it distinguishes between choice-specific and generic segmentation. Most applications of market segmentation have, justifiably, chosen as a basis variables that are sensitive to the specific behavioral choice the model deals with (e.g., automobile ownership for mode choice, life cycle and occupation for automobile ownership choice, etc.). Yet, conceptually as well as practically, a generic segmentation, one which is applicable to the whole range of travel-behavior models, is very attractive. Although a generic basis may lose its sensitivity to some specific choice situation, it can be practical for a wide range of applications.

There is general agreement that market segmentation is a useful technique to capture taste differences between population groups. As to segmentation basis, no single approach has been shown to be universally superior (5). The choice of segmentation basis thus depends on context and needs. One of the advantages of the technique is that it also provides a method for incorporating attitudinal data, as a basis for segmentation, in disaggregate revealed-preference models. To date, such information is not explicitly treated by disaggregate models.

Life-Style as a Segmentation Basis

Life-style is defined as the pattern of behavior that conforms to the individual's orientation toward the three major roles of a household member, a worker, and a consumer of leisure, and to the constrained resources available. A detailed discussion of the nature of these life decisions and the definitions of life-style is given elsewhere (11).

The choice of a life-style is a long-term one. Probably a person makes that choice only a few times in the course of life. By using the concept of a choice hierarchy that distinguishes between the mobility (long-term) and travel (short-term) decisions, as suggested by Ben-Akiva (12), it is suggested to add the choice of life-style (very long-term decisions) as an upper block in this hierarchy, as illustrated in Figure 1. The longer-term decision, that of choosing a life-style, constitutes a choice of the type or pattern of activities one aspires to engage in. It is the outcome of this choice that is the motivation for the observed mobility and travel.

If it is possible to identify life-style groups, i.e., groups that share similar patterns of behavior as defined above, then these groups can serve as market segments. They have the advantage that they share not only a common value on some socioeconomic variable but also similar motivations for travel.

METHODOLOGY

Two stages of analysis were employed in testing the hypotheses about the relevance of the life-style concept. First, a method for identifying life-style groups was developed. In the second stage, the life-style groups were tested as market segments in travel-behavior choice models.

Identifying Life-Style Groups

Given the above definition, life-style groups could presumably be identified by clustering of individuals or households for which we can observe similar patterns of life-style choices. However, in most available data sets, the orientation toward leisure is not measured.

Therefore, it becomes necessary to identify life-style groups by the use of proxy variables from which inferences on the choice of life-style can be made. A basic premise of this research is that the concept is to be developed within the commonly available urban transportation surveys (i.e., home interview survey).

It is assumed that membership in life-style groups can be estimated from an array of socioeconomic and demographic characteristics of a household. The choices noted in the definition of life-style are identified by surrogate variables that, as closely as possible, imply or indicate the individual's patterns of life-style aspirations.

The socioeconomic and demographic variables that were used to define life-style groups include the following:

1. Household structure
   a. Age of head of household (AGE)
   b. Presence of children under 6 years old (CHLDPR)
   c. Presence of children between 6 and 18 years old (JCHLD)
   d. Household size (HHSIZE)
   e. Number of adults in household (ADULTS)
2. Labor force participation
   a. Proportion of household income earned by male head of household (PRNC1)
   b. Proportion of household income earned by female head of household (PRNC2)
   c. Household annual income (INCOME)
   d. Employment status of male head of household (EMP1)
   e. Employment status of female head of household [full employment (FEMP2) and part-time employment (EMP2)]
3. Orientation toward leisure
   a. Level of education, highest in household (EDUCATION)
   b. Number of white-collar male employees (WCOL1)

The data set used in this analysis is the Baltimore travel-demand data set collected in 1977. It contained detailed one-day trip reports for some 965 households.

These variables, which serve as indicators of life-styles, were used to identify groups of households that share similar life-styles. The statistical method employed is cluster analysis (K-means method). Cluster analysis is an exploratory tool that enables the analyst to search for different structures that may exist in the data. Although cluster analysis can generate any desired output, and therefore should be used with much caution (13), its use can provide valuable insights into a population structure by varying the specification and the relative weight assigned to each variable. More details on the use of cluster analysis in this research are given elsewhere (11,14).

Use of Travel-Demand Model to Test Segmentation Schemes

Two approaches were employed to test the relevance of life-style segmentation. The first is the incorporation of interaction variables in the specification of the utility function. That is, some of the variables assumed to be of different value or importance to different life-style groups appear in the model as life-style-specific variables. The second approach involves the separate estimation of models for each market segment. Here the assumption is that all parameters vary across the life-style groups and therefore will assume different values in the estimation procedure.

The model is of a logit form that predicts the choice probability of a particular mode and destination combination. The choice set includes three modes--automobile, walk, and transit--as other modes constituted negligible numbers in the sample. The possible destinations included all traffic zones that have shopping facilities, although, for the purpose of estimation only, a sample destination was assigned to each individual, including the home zone, the central business district (CBD), the zone actually chosen, and a random sample of three or four zones.

RESULTS

Cluster-Analysis Output

As cluster analysis is an experimental technique, a large number of alternative outputs were produced and evaluated. From these, the clustering schemes described in Tables 1 and 2 provide two intuitively acceptable divisions among life-style groups in the current data set.

Scheme A

Under scheme A, five clusters were created based on 521 observations, each represented by 20 variables. The cluster means for each variable are presented in Table 1. In this scheme, two variables that describe time allocation to activities (home activities and services) were included for each of the heads of the household. In other schemes, time allocation was excluded because it may be viewed as part of the dependent variable.

The differences among the clusters can be characterized along a number of dimensions. For example, both cluster 1 and 2 are the upper-income groups, yet they vary in household size, the latter having children only in a small percentage of the sample. Also, the female spouse in cluster 2 is contributing significantly more than in any other cluster to the household income and, consequently, also spends the least time at home. Cluster 2 also includes the highest level of education and the largest share of time allocated to services for the household by the male head.

Cluster 1 includes the large household headed by middle-aged, educated persons. Women in this group rarely participate in the earning, yet the household income is relatively high and most of the male workers hold white-collar occupations.

Cluster 2 consists of very small households headed by middle-aged adults. It is impossible to infer from the data whether cluster 2 members were childless throughout their life or whether they are households with older children who have already left. Judging by income and education, clusters 1 and 2 probably belong to the same socioeconomic class, yet they differ in the females' work status and activity pattern and hence in life-style.

Cluster 3 is characterized primarily by its low income, low level of education, and its very low share of white-collar workers. The demographic information indicates that a third of this group are elderly households, and we tend to assume that actually two distinct household sizes constitute

Table 1. Clustering scheme A: mean values of input variables.

Cluster No.	No.	Percentage of Sample	HHSIZE	ADULTS	Age of Head Distribution (%) 18-44	45-65	65+	CHLDPR	JCHLD	PRNC1	PRNC2	Education Level Distribution (%) 1	2	3	4
1	161	31	5.16	2.9	0	99	1	100	93	2.32	3.13	2	35	46	17
2	75	14	2.47	2.3	21	71	8	13	11	3.47	1.61	13	37	27	23
3	71	14	3.11	2.1	10	59	31	49	39	1.97	2.70	100	0	0	0
4	108	21	3.87	2.0	100	0	0	92	49	2.00	3.07	4	42	45	9
5	106	20	2.58	2.5	0	70	30	8	1	2.28	3.49	1	49	42	8
Total	521	100	3.70	2.5	25	63	12	60	46	2.36	2.92	17	35	36	12
P-value			0.999	0.999	0.999	0.999		0.999	0.999	0.999	0.999	0.999	0.999	0.999	

Table 2. Mean values of variables by cluster: scheme B'.

Cluster No.	No.	Percentage of Sample	HHSIZE	ADULTS	Age of Head Distribution (%) 18-34	35-64	65+	CHLDPR	JCHLD	PRNC1	PRNC2	Education Level Distribution (%) 1	2	3	4
1	120	23	4.73	2.97	0	98	2	79	69	2.33	3.38	0	0	81	19
2	86	17	2.49	2.28	24	70	6	17	12	3.52	1.76	20	34	27	19
3	108	21	3.95	2.03	100	0	0	94	52	1.93	3.15	9	41	42	8
4	108	21	4.75	2.75	0	99	1	91	81	2.25	3.09	23	69	0	8
5	99	19	2.15	2.09	2	45	53	4	2	2.01	3.01	37	35	23	5
Total	521	100	3.71	2.45	25	63	12	60	46	2.36	2.93	17	35	36	12
P-value			0.999	0.999	0.999	0.999		0.999	0.999	0.999	0.999	0.999	0.999	0.999	

this group: elderly without children and middle-aged with children. The dimension that discriminates this group is obviously economic and educational, so this group can probably be labeled the low-socioeconomic class, which in terms of life-style is a group on which the economic constraint is most binding. It is also typified by a very low share of household services performed by the male head.

Cluster 5 is similar to cluster 3 in its age composition yet differs significantly in its economic and educational status and presence of children. Again, it is impossible to determine whether this is a lifelong childlessness or whether it is late-life childlessness.

Cluster 4 is distinguished from the others mainly by its young household composition. One can speculate that this group is the younger version of cluster 1, where the differences in household size, income, and participation in the labor force can mostly be attributed to the age difference.

In summary, we suggest that all but cluster 3 are groups of similar socioeconomic status that vary along demographic and activity dimensions to constitute different life-style groups. Cluster 3 forms a separate group because of its economic constraints but could probably include some distinct life-styles within it, which vary along similar lines that distinguish the rest of the clusters.

Scheme B'

Clusters 1 and 2 constitute the upper socioeconomic classes as judged by their income and educational levels. They are dissimilar in their demographic characteristics and employment status. Cluster 1 consists of middle-aged households (35-64 years old) and very large households. By contrast, cluster 2 consists of much smaller households and one-quarter of its members are young (less than 34 years old). The difference in employment and occupation status is also noticeable. Cluster 1 male members are primarily employed in white-collar jobs and a very small number of that cluster's female heads of households participate in the full-time labor force. This life-style group may be characterized as the family-oriented economically active group that, by virtue of being family-oriented, only the male head of household works outside the house while the female head is not committed to an out-of-home economic activity. This can be viewed as the traditional form of life-style for the family-oriented households, which contrasts with some emerging new forms of life-styles. Family orientation combined with dual participation in the labor force, which traditionally was observed only in the working classes, is today more prevailing in economically well-to-do households. In cluster 2, 95 percent of the female heads of households work full-time.

Cluster 2 is more heterogeneous than cluster 1. It probably captured both white- and blue-collar workers who have high incomes and whose female spouses work full-time. Hence, it could probably be broken down to at least two distinct groups. The first group is probably the newly emerging life-style of families headed by two career-oriented or other white-collar employees, many of whom do not have children. The second group is probably the households of the upper working class, where both heads work and hence have a relatively high income.

Cluster 3 is a younger group, mostly with young children and with very low rates of women participating in the labor force. It is thus assumed to be a younger version of cluster 1 members, for which the attainment of income and educational levels are a matter of time. It also includes a high proportion of blue-collar workers who will eventually belong to cluster 2 or 4. It is obvious that, in this case, life cycle is the dominant discriminatory dimension, and this group, regardless of economic status, can be defined as the young, family-oriented childbearing households.

Cluster 4 is similar in its demographic characteristics to cluster 1, but its members differ in socioeconomic attributes, where cluster 4 members constitute a lower-income, lower-educational level class. Women participation in the labor force in

INCOME ($)	Home 1	Home 2	Leisure 1	Leisure 2	Service 1	Service 2	EMP1	WCOL1
24 726	61	79			1.66	2.93	37	52
25 133	65	63			2.01	1.87	72	49
10 176	77	87			0.96	1.88	24	6
17 337	59	81			1.59	3.09	81	50
20 316	77	90			1.70	2.13	49	53
20 373	67	80			1.61	2.50	52	45
0.999	0.999	0.999			0.58	0.25	0.999	0.999

INCOME ($)	EMP1	WCOL1	FEMP2	EMP2
29 749	45	68	11	27
24 465	69	44	95	0
16 810	81	48	15	13
18 097	40	31	23	12
11 823	27	30	0	8
20 373	52	45	26	13
0.999	0.999	0.999	0.999	0.999

cluster 4 is higher in the full-employment category and lower in the part-time category, which indicates that there are more working-class households earning less for their work and working despite the high incidence of the presence of young children. This group, in reference to the life-style choice, includes those households that have chosen to establish a family with children and who have chosen, in most cases by default, to participate in lower-paying jobs in the labor market. Holding lower-paying jobs requires for this group's members that more than one family member will participate in the labor force.

Cluster 5 includes most of the elderly households of the sample, but almost half of it are middle-aged households. This cluster is distinct from the others by its low income and education levels, small household size (and almost no households with children), and very low levels of participation in the labor force. This cluster, it is assumed, captured both the retired low-income elderly and the poor middle-aged households. Thus, it is a cluster based on both socioeconomic and demographic attributes. A refinement of this cluster would probably reveal the retired people as one life-style group and the other as a group who have made a decision not to participate regularly in the labor force and not to have children. Their life-style can be characterized as that of living through life rather inactively. However, time limitation prevented us from this refinement at the current stage.

In summary, this scheme is discriminatory along a mixture of dimensions: purely socioeconomic, employment status, and age. It is thus probably closer to a life-style classification, which allows similar values on some attributes and discriminates on others, rather than to a socioeconomically based discrimination. Yet it is obvious that some groups are still quite heterogeneous, and the differentiation among them can only be obtained by increasing the number of clusters, which will result in identification of smaller but more distinct life-style groups.

Travel-Demand Models

For testing the viability of the life-style segmentation, a choice situation was desired, which was assumed to be sensitive to life-style differences and that had also been modeled before, so that the model specification is relatively known. Given the data available, that situation was the mode and destination choice for shopping trips, which was previously modeled by Adler and Ben-Akiva (15).

Two model structures were estimated. One is a three-mode model, in which the hypothesis that certain attributes of the utility function are affected by the membership in a particular life-style group was tested. The second structure included only the automobile and walk modes. For this model, the life-style-based segmentation was compared with a pooled sample and with other market segmentation schemes.

The variables used in the various models are defined in Table 3, and most of them are self-explanatory. Walk time was defined only for interzonal trips, because in the intrazonal trips we concluded that assigning a constant trip length involves a large error and would result in inconsistent coefficients. Thus, intrazonal walk time is captured by a constant term (INZWDM).

In the three-mode model, accounting for taste variation was obtained through the incorporation of life-style group-specific variables in the model. The hypothesis that certain variables interact with the various life-styles was tested by defining these as group specific (denoted by numbers 1 through 5 for the five life-style groups). The estimated coefficients and summary statistics of the three-mode case with and without the life-style-specific variables are presented in Tables 4 and 5. Although the improvement in the model performance (as evaluated by the log-likelihood ratio) could be attributed simply to the addition of relevant explanatory variables, the contribution of this analysis is in demonstrating the differences of some of the estimated coefficients across life-style groups. Specifically, the difference in the out-of-vehicle travel time for automobile (OVTTA) between groups 1 and 2 indicates, for example, a different evaluation of time for these, despite the fact that their average income is similar ($24 726 and $25 133, respectively). Such a difference may be attributed to the fact that these groups vary mainly in the presence of children, which is very low in group 2, and in the employment rate of the female head, which is very high in that group. (This result must be qualified because of the relatively low t-statistic for the OVTTA of group 2.)

The weight assigned to walk time also varies considerably between the life-style groups where group 3, which is the poorest, least educated, and least holding white-collar occupations, has the lowest negative value, and group 4, which is the youngest and has the highest employment rate, accounts for the highest negative value.

Th LNRET variable accounts for the size of the shopping opportunities at the destination. The variance in the coefficients among the groups should indicate varying preferences for shopping at large shopping concentrations, where group 1 is least sensitive to size. The sensitivity of group 4 may be explained by the fact that the members of this group make the least trips alone (i.e., 56 percent of the trips are accompanied by at least one family member). If that member is a child, it is plausible that many shopping opportunities in proximity will be more attractive than few opportunities.

The last attribute assumed to be different among life-style groups is the dummy for intrazonal desti-

Table 3. Variable names and definitions.

No.	Variable	Definition
1	IVTTA	In-vehicle travel time for automobile, minutes, one way
2	IVTTTR	In-vehicle travel time for transit, minutes, one way
3	OVTTA	Out-of-vehicle travel time for automobile, minutes, one way
4	OVTTTR	Out-of-vehicle travel time for transit, minutes, one way
5	ACSTI	Out-of-pocket travel cost for automobile, one way, dollars, divided by annual income
6	COSTIN	Out-of-pocket travel cost, all modes, one way, dollars, divided by annual income
7	WLKTT	Walk-trip time for interzonal trips, 0 for intrazonal trips
8	LNRET	Natural LOG of retail employment in destination zone
9	RTDNS	Retail employment divided by total employment at destination zone
10	AUTOCON	Constant: 1 if automobile alternative, 0 otherwise
11	WLKCON	Constant: 1 if walk alternative, 0 otherwise
12	CBDDUM	Constant: 1 if CBD destination, 0 otherwise
13	INZDUM	Constant: 1 if trip destination equal to origin zone, 0 otherwise
14	INZWDM	Dummy for intrazonal walk trip: 1 if intrazonal walk trip, 0 otherwise
15	AAVAPR	Automobile availablity divided by number of adults in household for automobile alternatives
16	AAVWPR	Automobile availability divided by number of adults in household for walk alternatives
17	DRESW	Dummy for residential zone origin for walk alternatives: 1 if origin in zone of residence, 0 otherwise
18	SUBWLK	Dummy for walk alternatives in suburbs: 1 if origin in suburb, 0 otherwise
19	EMPAUTO	Dummy for employment status for automobile alternatives: 1 if fully employed, 0 otherwise

Table 4. Comparison of three-mode model with and without interaction of life-style.

	Without Life-Style Variables		With Life-Style Variables	
Variable	Estimated Coefficient	t-Statistic	Estimated Coefficient	t-Statistic
IVTTA	-0.167	-8.29	-0.173	-8.26
IVTTTR	-0.054	-1.39	-0.069	-1.72
OVTTA	-0.572	-4.70	-	-
OVTTTR	-0.108	-1.60	-0.102	-1.67
WLKCON	-0.644	0.73	0.531	0.59
AUTOCON	2.200	2.43	1.964	2.12
INZDUM	-3.070	-12.33	-	-
INZWDM	0.543	0.10	0.087	0.15
EMPAUTO	0.741	1.78	0.692	1.60
COSTIN	-7522	-1.20	-6169	-0.96
ORESW	1.953	3.81	1.970	3.74
SUBWLK	-1.000	-2.26	-1.089	-2.40
AAVAPR	3.046	2.83	3.838	3.40
AAVWPR	2.888	2.78	3.750	3.41
CBDDUM	-0.851	-1.85	-0.933	-1.86
RETDENS	0.967	2.55	0.972	2.49
LNRET	0.410	5.65	-	-
WLKTT	-0.074	-5.10	-	-
OVTTA1			-1.078	-3.42
OVTTA2			-0.242	-1.91
OVTTA3			-0.426	-1.04
OVTTA4			-1.028	-2.52
OVTTA5			-0.970	-2.64
WLKTT1			-0.096	-3.64
WLKTT2			-0.113	-1.71
WLKTT3			-0.031	-2.02
WLKTT4			-0.136	-3.46
WLKTT5			-0.115	-3.48
LNRET1			0.286	2.74
LNRET2			0.425	2.44
LNRET3			0.368	1.62
LNRET4			0.712	4.69
LNRET5			0.456	2.83
INZDUM1			-3.792	-9.26
INZDUM2			-2.682	-5.76
INZDUM3			-2.385	-4.40
INZDUM4			-3.023	-7.73
INZDUM5			-2.974	-7.15

nation compared with the other alternatives. (Note that by including the intrazonal destination in the choice set for all observations, this and the CBD destination are disproportionately represented in the sample and therefore have biased coefficients.) With all coefficients highly significant, we find a range of coefficients that vary from -3.79 for group 1 to -2.38 for group 3. The fact that the latter is the group with the lowest automobile-ownership level and the lowest coefficient for walk time explains, in part, its low negative value for the intrazonal shopping trip.

Table 5. Summary statistics for Table 4.

Item	Without Life-Style Variables	With Life-Style Variables
L^*0	973.427	973.427
$L^*\theta$	434.6	412.75
ρ^2	0.554	0.576
Adjusted ρ^2	0.530	0.531

In summary, this analysis demonstrates that the values of the coefficients estimated in a model can be disaggregated into very different values by interacting the variables with group indicators that are a priori assumed to be behaviorally different. The effect of this disaggregation on the remaining variables must also be noted. The improved accounting for the distractions to walk trips by separating the walk-time variables results in the reduction of the magnitude of the walk constant, as more of the variance is explained by the interaction variables. Similar effects are visible in the case of the intrazonal walk dummy and the out-of-pocket cost variable (the latter is statistically insignificant). The observed differences in the estimated coefficients lead to the conclusion that the life-style groups are behaviorally relevant and that by using knowledge of life-style membership, the performance of the model is improved.

By using the market-segmentation approach, these schemes were evaluated. First, the life-style segmentation for the estimated model coefficients and some statistical properties of the models are presented in Tables 6 and 7. The pooled model included the total sample (344 trips), while models 1 to 5 correspond to each of the life-style groups presented in Table 2.

This set of models performs better than the pooled model, as evaluated by the value of the log-likelihood function: -342.8 as compared with -400.5 for the pooled model. The segmented models are performing better than the pooled model at a significance level of 0.001 (chi-square value of 115.3 with 54 df).

The life-style segmentation scheme was compared with two other segmentation schemes. The two were chosen from the variety of available schemes on the basis of the type of data they employ (i.e., available socioeconomic data), so as to be comparable with the life-style segmentation.

In the income-based segmentation, five income groups were defined and models were separately estimated for each. The estimated coefficients and summary statistics are shown in Tables 8 and 9. For the set of five models, the total value of the log-likelihood function is -373.9 as compared with -342.8 for the life-style segmentation. Note that a slight variation is due to the difference of one in the sample size (345 versus 344 cases).

The second segmentation scheme, which is a more elaborate one, is based on life cycle and occupation. This scheme was previously employed in a model of automobile ownership and mode of travel to work by Ben-Akiva and Lerman (7). The five segments are defined in Tables 10 and 11 with the list of estimated coefficients and summary statistics. This set

Table 6. Estimated coefficients for pooled sample and life-style segments.

			Life-Style Segment									
	Pooled Model		1		2		3		4		5	
Variable	Estimated Coefficient	t-Statistic	Estimated Coefficient	t-Statistic	Estimated Coefficient	t-Statistic	Estimated Coefficient	t-Statistic	Estimated Coefficient	t-Statistic	Estimated Coefficient	t-Statistic
IVTTA	-0.172	-8.13	-0.247	-4.32	-0.056	-1.28	-0.152	-3.43	-0.266	-5.42	-0.149	-2.12
OVTTA	-0.493	-3.90	-0.832	-2.02	-0.110	-0.57	-1.655	-1.96	-1.631	-2.31	-1.891	-1.72
SUBWLK	-1.043	-2.40	-3.303	-1.92	2.268	1.33	-2.546	-2.03	1.25	0.72	-0.320	-0.33
INZWDM	0.708	1.29	-2.415	-0.67	-7.798	-1.47	0.689	0.44	4.636	2.99	-0.462	-0.36
INZDUM	-3.161	-12.34	-4.484	-6.69	-1.995	-3.570	-2.901	-5.54	-3.742	-6.34	-3.943	-4.53
AAVAPR	0.135	0.21	-4.152	-2.19	2.582	0.89	0.140	0.01	3.718	1.52	0.449	0.37
AUTOCON	1.619	2.23	2.566	0.58	-6.534	-1.10	2.571	1.25	6.682	3.09	1.009	0.60
ACSTI	-6668.26	-1.00	1183	0.07	-49 043	-2.07	-6966	-0.51	9852	0.99	-16 633	-0.84
LNRET	0.403	5.47	0.401	2.84	0.231	1.25	0.637	3.82	0.114	0.679	0.761	3.18
RTDNS	0.889	2.28	1.023	1.10	0.836	0.80	1.323	1.45	1.89	2.2	-0.44	-0.04
WLKTT	-0.065	-4.58	-0.402	-1.47	-0.555	-1.23	-0.109	-2.19	0.013	0.86	-0.128	-3.04
ORESW	2.328	4.31	5.451	2.33	3.243	1.65	3.187	2.47	3.024	2.13	1.97	1.63
EMPAUTO	0.599	1.42	0.973	0.727	2.000	1.30	-0.398	-0.38	0.498	0.43	-1.107	-1.15
CBDDUM	-1.476	-2.63	-0.203	-0.09	-1.158	-0.85	-[a]	-[a]	-[a]	-[a]	-3.726	-2.54

Note: The number of observations is as follows: pooled = 344, 1 = 50, 2 = 83, 3 = 82, 4 = 77, and 5 = 52.
[a]Variable excluded.

Table 7. Summary statistics for Table 6.

		Life-Style Segment				
Item	Pooled Model	1	2	3	4	5
$L^*(0)$	751.580	182.291	111.793	179.252	170.52	107.874
$L^*(\theta)$	400.462	70.102	66.667	84.418	72.361	49.345
ρ^2	0.467	0.62	0.40	0.53	0.58	0.54

Table 8. Estimated coefficients for models based on income segmentation and pooled model.

	Pooled Model		1		2		3		4		5	
Variable	Estimated Coefficient	t-Statistic	Estimated Coefficient	t-Statistic	Estimated Coefficient	t-Statistic	Estimated Coefficient	t-Statistic	Estimated Coefficient	t-Statistic	Estimated Coefficient	t-Statistic
IVTTA	-0.173	-8.17	-0.389	-1.74	-0.122	-2.39	-0.168	-4.29	-0.130	-1.93	-0.194	-4.54
OVTTA	-0.496	-3.91	-1.365	-1.55	-0.354	-1.37	-[a]	-[a]	-1.016	-2.04	-0.315	-1.14
SUBWLK	-1.052	-2.42	-[a]	-[a]	0.499	0.41	-1.499	-1.97	-0.897	-0.71	-[a]	-[a]
INZWDM	0.691	1.26	0.033	0.02	-2.522	-0.96	3.694	3.31	-4.379	-1.76	3.465	1.07
INZDUM	-3.147	-12.33	-4.182	-3.25	-2.717	-4.82	-3.460	-6.86	-2.394	-4.35	-3.970	-6.73
AAVAPR	0.126	0.20	0.561	0.31	6.631	2.47	-0.646	-0.58	-2.155	-1.55	-3.760	-1.37
AUTOCON	1.629	2.24	1.166	0.63	-3.822	-1.37	3.891	2.84	0.241	0.10	9.620	2.07
ACSTI	-6449	-0.97	-48 398.8	-0.67	-20 961.9	-1.29	-10 989.7	-0.95	-27 802.0	-0.87	-6140.63	-0.40
LNRET	0.407	5.53	0.769	1.54	0.529	2.76	0.236	2.05	0.303	1.87	0.268	1.95
RTDNS	0.893	2.29	1.361	0.77	1.769	1.83	2.684	3.93	0.427	0.55	0.578	0.63
WLKTT	-0.065	-4.59	-0.131	-3.03	-0.195	-1.89	-0.001	-0.08	-0.332	-1.86	-0.021	-0.37
ORESW	2.333	4.31	-[a]	-[a]	3.758	2.69	1.577	1.70	-[a]	-[a]	5.821	2.83
EMPAUTO	0.609	1.44	0.612	0.54	-2.958	-2.29	0.799	1.03	-[a]	-[a]	1.248	0.74
CBDDUM	-1.482	0.2165	-3.883	-2.24	-1.417	-0.87	-[a]	-[a]	1.257	0.64	-0.862	-0.46

Notes: For income segmentation, 1 = low income and 5 = high income.
The number of observations is as follows: pooled = 345, 1 = 38, 2 = 68, 3 = 102, 4 = 58, and 5 = 79.
[a]Variable excluded.

Table 9. Summary statistics for Table 8.

Item	Pooled Model	1	2	3	4	5
$L^*(0)$	753.785	74.2404	150.219	223.517	130.679	175.13
$L^*(\theta)$	401.312	25.427	71.982	123.095	67.569	85.865
ρ^2	0.468	0.658	0.521	0.449	0.483	0.510

Note: For income segmentation, 1 = low income and 5 = high income.

Table 10. Estimated coefficients for life-cycle and occupation segments and pooled model.

	Pooled Model		1[a]		2[b]		3[c]		4[d]		5[e]	
Variable	Estimated Coefficient	t-Statistic	Estimated Coefficient	t-Statistic	Estimated Coefficient	t-Statistic	Estimated Coefficient	t-Statistic	Estimated Coefficient	t-Statistic	Estimated Coefficient	t-Statistic
IVTTA	-0.173	-8.17	-0.142	-4.14	-0.240	-4.08	-0.225	-3.24	-0.057	-1.04	-0.261	-4.63
OVTTA	-0.496	-3.91	-1.356	-2.56	-0.315	-1.10	-0.153	-0.88	-0.660	-2.02	-2.00	-1.80
SUBWLK	-1.052	-2.42	-0.768	0.88	-0.937	-0.77	-0.949	-0.78	-0.465	0.37	-2.54	-1.95
INZWDM	0.691	1.26	1.169	0.76	3.950	3.29	-2.33	-1.28	-5.222	-2.11	0.242	0.14
INZDUM	-3.147	-12.33	-3.660	-7.45	-3.442	-5.72	-3.08	-4.75	-2.169	-3.39	-4.039	-5.30
AAVAPR	0.126	0.20	-0.614	-0.50	-1.223	-0.73	-0.742	-0.42	3.968	1.42	2.712	1.33
AUTOCON	1.629	2.24	3.164	1.70	7.586	3.45	0.910	0.42	-5.388	-1.86	-0.230	-0.09
ACSTI	-6449	-0.97	-12 493	-1.05	-398	-0.02	-2545	-0.11	-31 563	-1.59	10 120	0.96
LNRET	0.407	5.53	0.487	3.89	0.431	2.08	0.426	2.09	0.569	2.61	0.295	1.70
RTDNS	0.893	2.29	1.403	2.11	1.007	1.03	1.219	1.05	0.294	0.29	0.215	0.18
WLKTT	-0.065	-4.59	-0.100	-1.90	0.009	0.71	-0.114	-2.49	-0.409	-2.64	-0.083	-2.00
ORESW	2.333	4.31	3.144	2.52	1.627	1.10	4.442	2.35	2.530	1.96	-0.412	-0.222
EMPAUTO	0.609	1.44	1.683	1.48	-1.42	-1.11	-0.030	-0.03	-1.307	-1.04	1.843	1.40
CBDDUM	-1.482	0.2165	-[f]	-[f]	-2.41	-1.59	-1.892	-1.77	-[f]	-[f]	-0.742	-0.51

Note: The number of observations is as follows: pooled = 345, 1 = 113, 2 = 68, 3 = 52, 4 = 51, and 5 = 56.

[a]Young white-collar with and without children.
[b]Young blue-collar with children.
[c]Old white-collar without children.
[d]Old blue-collar without children.
[e]Old blue- and white-collar with children.
[f]Variable excluded.

Table 11. Summary statistics for Table 10.

Item	Pooled Model	1	2	3	4	5
$L^*(0)$	753.777	251.066	146.088	124.485	108.624	123.515
$L^*(\theta)$	401.312	116.551	70.9242	66.729	54.3713	57.2442
ρ^2	0.468	0.536	0.515	0.464	0.499	0.537

Note: Segments 1 through 5 correspond to footnotes a through e in Table 10.

Table 12. Summary statistics of alternative market-segmentation schemes.

Scheme	ρ^2	Log-Likelihood Difference (versus pooled)
Pooled	0.47	
Income segmentation	0.50	54.8
Life-cycle and occupation segmentation	0.51	71.8
Life-style segmentation		
A	0.58[a]	43.7
B′	0.54	115.3

[a]Compared with 0.55 for the pooled three-mode model.

of models resulted in a total log-likelihood value of -365.8 as compared with -342.8 for the life-style segmentation. Thus, the life-style segmentation performs significantly better than the income and life-cycle/occupation segmentations. The summary statistics are presented in Table 12.

In assessing the individual life-style-based models shown in Tables 6 and 7, one notices that they vary in their explanatory power as evaluated by the ρ^2 statistic. The range is from $\rho^2 = 0.62$ for model 1 to $\rho^2 = 0.40$ for model 2. Recall that segment 2 is that of a relatively high socioeconomic class that is distinguished from segment 1 mainly by the high rate of females' full employment and small one-household size. It was speculated above that segment 2 includes at least two distinct groups that vary in life-style and in tastes. Consequently, constraining the model coefficients to be identical for these two (or more) groups results in a relatively low explanatory power.

Most cofficients have the expected sign, and those that do not have very low t-statistics. Overall, the problem of sample size becomes obvious here, as each segment is based on less than 100 observations and 14 coefficients are estimated, the standard errors for most being relatively large.

CONCLUSION

The results shown in this research have demonstrated that the life-style concept, as operationalized here, does provide an improved discrimination between market segments when compared with income or life-cycle/occupation-based segmentations. But it can be argued that the operationalization presented here is merely a more complex form of presenting socioeconomic characteristics, and the improvement in the model's performance could be attributed to the fact that more variables are taken into account.

Such arguments are refuted because the theoretical concept of life-style developed in this research does extend our conceptualization of travel-behavior decisionmaking. It suggests a sound theory of the relation between long- and short-range choices made by individuals. It also conforms with efforts carried out in other social sciences to improve the differentiation among behavioral groups (3,16). Hence, this work is a step in the direction of identifying an array of variables that reflect, through some interaction, the chosen life-style of groups of individuals, and they are not merely a combination of some available variables.

The operationalization presented here still lags after the theoretical concept. Further research is being done in an effort to improve the ability to distinguish between life-styles emerging in Western society today. Specifically, it is now necessary to identify variables that are more indicative of life-style and to attempt to identify life-style segments within a relatively homogeneous socioeconomic sample.

ACKNOWLEDGMENT

The paper is based primarily on research done at the Massachusetts Institute of Technology (MIT) and supported by a grant from the U.S. Environmental Protection Agency. We wish to thank Marvin L. Manheim and Steve Lerman of MIT and David Segal of Harvard

University for their useful comments and suggestions.

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Publication of this paper sponsored by Committee on Passenger Travel Demand Forecasting.