Transportation Research Record 605, 1976, pp. 29-34.
3. Calibrating and Testing the Gravity Model for Any Size Urban Area. Bureau of Public Roads. U.S. Department of Commerce, Washington, D.C., 1965.
4. K. E. Heanue and C. E. Pyers. A Comparative Evaluation of Trip Distribution Procedures. HRB, Highway Research Record 114, 1966, pp. 20-37.
5. Urban Transportation Planning. Federal Highway Administration, March 1972.
6. J. F. Morrall and others. Traffic Prediction Models for Central Business District Planning. Proc., Fourth Conference, Australian Road Research Board, Melbourne, 1968.

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Population Segmentation in Urban Recreation Choices

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The paper describes an investigation of various segmentation bases for capturing the behavioral differences in urban recreation demand. The analysis and evaluation of the segmentation bases were mainly achieved through the calibration of disaggregate quantal choice models (by using the multinomial logit technique) for each population segment and statistical comparison of these models and their estimated coefficients. After a preliminary elimination, three segmentation bases were selected for detailed evaluation: stage in the family life cycle, recreation-activity attractiveness, and geographic location. For each of the categories of these bases, a recreation-activity choice (a detailed trip-purpose) model was calibrated. These segment models were then compared with the pooled model both in terms of the overall goodness of fit and in terms of the differences in their coefficient estimates. Each of the segmentation schemes that was tried revealed significant differences and most of these differences bear plausible relation to the segmentation variables. Significant behavioral variations, which may result from differences in tastes, motivations, and personalities, may be captured through population segmentation.

Recreation is a broad and diverse area of human activity, encompassing a wide range of pursuits. Increased demand for participation in these activities creates, in varying degrees, increased use of transportation facilities. Visits to national parks alone have increased at an annual growth rate of about 7.5 percent in the period from 1957 through 1976 (1, 2). This is considerably higher than the population growth rate during the same period and also implies a very considerable growth rate in the consumption of fossil fuels for recreation activities.

The concern of the research in this paper is urban recreation and cultural activities. Most work on demand for recreation has concentrated on nonurban recreation and vacation activities (3-5), although many government units in urban areas are becoming increasingly concerned about issues of policy and investment in recreation facilities. If in the future transportation fuels are less available or the costs of such fuels are increased significantly, urban recreation facilities will probably receive the impacts of resulting changes in travel behavior. This will occur because travel to recreation is one type of travel most likely to be reduced or diverted from far sites to near ones (urban) in the event of high price or low availability of fuel. From a policy viewpoint, freedom to participate in a wide range of recreation activities may be considered to be one element of the high living standards enjoyed in the United States and Canada. Thus, substitution of local (urban) recreation activities for long-distance ones may be one way to prevent energy scarcity or high prices from eroding living standards.

This research introduces market segmentation as a means to understand and analyze recreation travel behavior. However, the paper deals only with recreation-activity choice (i.e., a detailed trip purpose) for a variety of reasons:

1. The reasons why people engage in recreation activities are much more complex, diverse, and numerous compared to other trip purposes. Recreation activities can be undertaken simply for fun or to fulfill various other complex psychological matters such as needs, motivations, and values. Hence, the consequences of recreation travel can only be understood after recreation behavior, per se, is understood. This is perhaps more crucial than for any other trip purpose.
2. Recreation is a gross trip purpose. The activities covered include a wide variety of activities and widely varying needs for travel, ranging from skiing to watching television. Thus, activity choice becomes an important issue, especially for the resulting travel implications.
3. We believe that the differences in individual tastes, motivations, and perceptions are the greatest influences on activity choice and, hence, concentrating on this choice can show the effects of segmentation more clearly.
4. The passage to recreational travel demand from recreation demand is a relatively trivial matter.

The basic demand-modeling hypotheses, which are described elsewhere (6), assume that both characteristics of the individual and attributes of the alternatives affect the choice process. Several mechanisms may be argued for the process by which these characteristics influence choices. One possibility is to use these characteristics as linear, additive terms in the utility function of the recreation activities. In this case, the effect of the characteristics is marginally to add to or subtract from the utility of activities and to affect the relative tastes of individuals for different attributes. Watson and Stopher (7), inter alia, argue that this is not the most appropriate manner in which to portray the effects of these variables. Rather, they argue that the appropriate manner to enter the variables is to use them as a basis for population (market) segmentation. This has also been argued extensively as a basis for improving the capability and responsiveness of individual choice models (8, 9).

The data for this research consist of 812 cases from two suburbs of Chicago: Evanston and Des Plaines. They provide information on the perceptions of attributes, availabilities, attractiveness, and annual and seasonal participation for selected recreation activities. In addition, data were obtained on socioeconomic characteristics of respondents. Some of the questions in the survey pertain to a list of 17 activities that were determined to represent a majority of urban recreation pursuits; however, perceptions of the attributes were obtained for only three activities, which were selected by each respondent as his or her most frequent recreation activities. The attributes include physical measures, such as distance traveled to the site, fee paid, and duration, and 23 conceptual items, which were rated on a five-point Likert scale that covers a range of agreement from strongly agree to strongly disagree.

One of the principal tasks of this research was to determine the feasibility of transferring the technology of individual choice modeling from travel demand to recreation demand by using the multinomial logit model (10-12). This technique can be expressed mathematically as

$$P(i; A_t) = \exp[V(Z_i, S_t)] \Big/ \sum_{j \in A_t} \exp[V(Z_j, S_t)] \tag{1}$$

where

$P(i; A_t)$ = the probability that recreation alternative i is chosen by consumer t from his or her choice set (A_t),

$V(Z_i, S_t)$ = systematic (nonrandom) part of the utility,

Z_i = vector of attributes of recreation alternative i, and

S_t = vector of characteristics of individual t.

In this project, further support for segmentation is provided by the models built on the Evanston and Des Plaines data sets, which revealed substantial differences; however, these differences were also found in the distributions of various characteristics of respondents from the two locations. It seems reasonable to postulate that the observed differences may, therefore, be due to different distributions of tastes for recreation-activity attributes in the two suburbs. Also note that McFadden, Tye, and Train (13) have shown that treatment of a heterogeneous population as a homogeneous one results in case 2 violations of the independence of irrelevant alternatives property of multinomial logit models and leads to biased coefficient estimates and a pattern of overprediction and underprediction. Hence, population segmentation is necessary in order to reduce the likelihood of bias in the fitted models. (Of course, if no differences are found in the fitted coefficients of models from different segments, it may be postulated that the population is homogeneous and that case 2 violations from this cause are not present.)

HYPOTHESES OF SEGMENTATION

A number of hypotheses relating to population segmentation can be tested. First, a number of variables may be considered as bases for segmentation, including available socioeconomic characteristics (income, age, sex, and stage in the family life cycle) and situational or taste variables (geographic location, importance of recreation activities, and activity attractiveness, subjectively rated). In travel-forecasting work, results have been rather inconsistent with socioeconomic variables (7, 14-16). Nevertheless, it seems appropriate to test such variables because some can readily be hypothesized to have an effect on participation in recreation activities. The first hypothesis is, therefore, that socioeconomic and situational or taste variables can be used as a basis for population segmentation and will reveal significant differences in recreation-choice behavior. This hypothesis can be tested partially by analyzing variations in participation rates for different activities over the ranges of selected segmentation variables. Methods for this include simple graphical and cross-tabular presentations and analysis of variance.

The second hypothesis arises from the treatment of the ratings of the 23 conceptual attributes of recreation activities. These fundamental attributes should not be used in modeling because their individual reliabilities are very low, as has been established in psychometric theory (17); because they relate to a few underlying salient concepts that are formed by groups of the fundamental attributes; and because the evaluative space of an individual is believed to be quite limited in its number of dimensions, and these dimensions represent the salient concepts. The salient concepts can be identified by multidimensional scaling, individual scaling, and factor analysis. Previous work (18, 19) has shown factor analysis to be an acceptable procedure that is cheaper and less subject to limitations than the scaling procedures, and it was therefore used in this study (6). Three-factor solutions were used for all analytical work because these solutions appeared to meet all of the criteria set for selecting the most efficient space.

The second hypothesis, which arises from this, is that different population segments operate with different perceptual spaces and, hence, different factor structures. Although a statistical test for different factor structures has been suggested recently (20), this hypothesis was not tested in this research for three reasons: (a) Allaire (21) and Hauser (22) have shown that in consumer marketing it is reasonable to assume homogeneous perceptual spaces but with heterogeneous preference parameters; (b) some preliminary investigations of heterogeneity on two of the segmentation variables failed to reveal any apparent differences in the perceptual spaces for the data of this project; and (c) the adoption of an assumption of heterogeneous perceptual spaces would invalidate the use of the other statistical tests of comparison used in this research. Therefore, a homogeneous perceptual space was assumed for all segments.

It may be postulated that different segments will weigh various attributes differently in the recreation-participation model. This hypothesis may be tested by building models of the same specification for each selected population segment. Statistical tests, using Student's t-distribution, may be conducted on the coefficients of different segments by using Equation 2.

$$t = (a_k^m - a_k^n) / \sqrt{(\sigma_k^m)^2 + (\sigma_k^n)^2 - 2\mathrm{cov}(a_k^m, a_k^n)} \tag{2}$$

where

a_k^m, a_k^n = coefficients for attribute k from the mth and nth segments,

Table 1. Geographic segmentation models.

	Segments					
	Pooled Model (812 cases)		Des Plaines (395 cases)		Evanston (414 cases)	
Variable[a]	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value
ACHV	0.283	15.3	0.335	9.9	0.258	10.4
EXTR	0.102	5.3	0.231	7.1	0.017	1.0
PAST	0.061	3.5	0.278	9.0	-0.062	2.8
ATTR	0.249	17.9	0.338	15.1	0.190	10.2
AVAIL	-0.057	5.2	-0.136	7.9	0.018	1.1
FEINC	-0.088	1.8	-0.046	0.8	-0.307	3.1
DISTLDA	-0.0002	1.9	-0.0006	4.0	0.0004	2.3
CARLDA	0.041	1.8	0.051	1.4	0.038	1.1
GOLFAGE	0.008	4.1	0.015	5.0	-0.002	0.8
EDCULT	0.117	2.1	-0.148	1.6	0.197	2.4

[a] The alternative specific constants have been excluded for space considerations.

σ_k^m, σ_k^n = standard errors of the coefficients, and

$\mathrm{cov}(a_k^m, a_k^n)$ = covariance of the coefficients a_k^m and a_k^n.

If the segments can be considered to be independent samples, the covariance term can be ignored (and, in practice, usually is).

In addition, likelihood-ratio tests can be performed between the pooled results of the segments and an unsegmented model. Minus twice the logarithm of the likelihood ratio ($-2 \log \lambda$) has been shown by Theil to be distributed like chi-square, with degrees of freedom equal to the difference between the sum of the number of fitted parameters of the segmented models over all segments and the numbers in the unsegmented model [i.e., $N_p(N_g-1)$, where N_p is the number of parameters and N_g is the number of segments or groups used].

The likelihood-ratio test, in this case, establishes whether or not the segmented models succeed in explaining more of the behavior than does the single unsegmented model. If the value of $-2 \log \lambda$ for the unsegmented model and the segmented models exceeds the table value of chi-square at a given significance level, then the null hypothesis (that segmentation provides no improvement in explanation of the phenomenon) can be rejected at that confidence level.

It may also be postulated that different segments of the population have different choice mechanisms, as would be shown if models with different specifications provide the best fit for different segments. This hypothesis is somewhat more difficult to test than was the preceding one. Rigorous statistical tests can be made only if the specification of the best model contains variables that represent a subset of those used under the preceding hypothesis or if the model from the preceding hypothesis is a subset of the best model. Otherwise, judgment would have to be on the basis of predictive performance and other similar properties.

In this research it was assumed that the perceptual spaces were common to all groups of the population and that all segments have the same choice mechanisms. Thus, it was necessary to find the best specification for a model to test for different weights on given attributes.

The search for the best model was done on the pooled data of the Evanston and Des Plaines suburbs. The steps in model development can be found elsewhere (6), and this model is reported later in this paper. The same model specification was used in all segmentation tests to facilitate the statistical testing of the hypotheses.

POPULATION SEGMENTATION

Seven segmentation variables were examined initially: income, age, sex, importance of recreation, stage in family life cycle, location, and attractiveness. Before the models were tested, however, cross-tabulations and one-way analysis-of-variance tests were made to detect interactions between the variables and activity-participation rates and to determine the levels at which to segment the variables. A constraint on the segmentation was imposed as a result of the relatively small size of the entire sample. A minimum sample of 100 cases was thought desirable, and a maximum of 812 cases was available from the entire data set. From this initial analysis, the most promising segmentation bases were found to be life-cycle stages, attractiveness, and geographic location.

In all of the models reported, a pooled three-factor structure was used in the best specification that was found for the unsegmented data. The dependent variable used in the model was summer participation (number of days on which the respondent had participated) for each of 10 reported activities—bowling; bicycling; swimming; playing tennis; playing golf; fishing; going to movies; going to theater, opera, or concerts; watching sports; and participating in team sports. The selection of these activities is reported elsewhere (6). The independent variables are listed and defined below.

ACHV—Achievement factor;
EXTR—Extroversion factor;
PAST—Pastoralism factor;
ATTR—Reported attractiveness of the activity;
AVAIL—Reported availability of the activity;
FEINC—Participation fee divided by annual gross income;
DISTLDA—Distance traveled to the activity for long- and medium-distance activities (i.e., swimming; playing golf; fishing; attending theater, opera, or concerts; and watching sports; 0 for other activities);
CARLDA—Number of automobiles available for long- and medium-distance activities, 0 otherwise;
GOLFAGE—Age for golf, 0 otherwise; and
EDCULT—Level of education for attending theater, opera, or concerts; 0 otherwise.

Geographic Segmentation

The models for geographic segmentation are shown in Table 1. The log-likelihood test between the geographic segments and the pooled model produces a value of 306 (this is the adjusted value for the difference in the numbers of observations for chi-square with 19 degrees of freedom. At 99 percent, the table value of chi-square is 36, so that the segmentation has clearly improved the model significantly. t-tests were also made for differences between individual coefficient values. The results of these tests are given below. It can be seen that all but two of the variables are significantly different at better than 95 percent confidence (t-value of the difference is less than 1.96).

Variable	t-Value	Variable	t-Value
ARCHV	2.49	FEINC	2.23
EXTR	5.06	DISTLDA	4.28
PAST	8.97	CARLDA	0.27
ATTR	5.11	GOLFAGE	0.32
AVAIL	6.59	EDCULT	2.80

In summary, geographic segmentation shows significant differences and improves the performance of the models. Variations are found both in the weights given to different recreation factors and to the weights of situational variables for the two segments.

Attractiveness Segmentation

As noted, the attractiveness segmentation appeared likely to be reasonably useful and represents the best approximation to a personality segmentation that can be achieved from these data.

Segmentation on attractiveness was undertaken through further analysis of the attractiveness scores on each activity. First, activities were grouped in terms of attractiveness. This is necessary for a number of reasons. Pragmatically, to use the 10 separate activities would generate a minimum of 100 (10^2) segments, where these would be defined according to a low or high attractiveness rating on each activity. Clearly, the data set is inadequate in size to support such a segmentation. All of those segments would probably not be populated because several activities would have sufficient segments in common that similar ratings would be given to activities that fall in particular groups. Also, the reliability of attractiveness scores for individual activities will probably be relatively low and would be improved by grouping similar activities and by using an aggregate rating for each group and individual. If activity groups are used, people would then be grouped according to the attractiveness scores that they gave to the different activity groupings. Activity groupings were obtained by subjecting the raw attractiveness scores to cluster analysis. These clusters are shown in Table 2. The first two clusters are considered to be reasonably consistent internally and also represent intuitively plausible clusters: The first cluster is social-cultural activities, and the second is outdoor (pastoral) sports. The third cluster is less consistent and less easily identified and was not used for segmentation.

The next step in the process was to find values of each attractiveness cluster that could be used for segmentation purposes. To do this, attractiveness scores were summed for each individual for the activities in each of the two clusters and then plotted on a scatter diagram, from which the data were divided into four approximately equal-sized groups (quadrants) for population segmentation, as shown in Table 3.

By using the same model specification as for the geographic segments, models were built for each of the four attractiveness segments, as shown in Table 4. The same likelihood-ratio test was carried out to determine if the segmented models together were able to explain more of the choice variation than was the pooled model. The adjusted value of $-2 \log \lambda$ for the test was found to be 492, which is substantially larger than the 99.5 percent table value of chi-square (of 88) for 57 degrees of freedom. Hence, the attractiveness segmentation can again be said to offer a significant improvement in the model performance.

Table 5 shows the results of t-tests for similarity of coefficients. It can be seen that 4-7 of the 10 vari-

Table 2. Attractiveness activity clusters for segmentation of pooled data.

Cluster	Activity	Internal Consistency (α)
Social-cultural (SOCATT)	Visit museum or art gallery; attend theater, opera, or concert; visit zoo; go to movies; picnic; and dance	0.70
Outdoor-sports (SPATT)	Bicycle, swim, play tennis, jog, and sail	0.65
Recreational activities	Watch sports, play team sports, bowl, fish, golf, and motorboat	0.58

Table 3. Attractiveness segments for pooled data.

Segment	Attractiveness Score: Social-Cultural	Attractiveness Score: Outdoor Sports
1	Low ≤ 19	Low ≤ 13
2	Low ≤ 19	High > 13
3	High > 19	Low ≤ 16
4	High > 19	High > 16

Table 4. Attractiveness segmentation models.

	Pooled Model (812 cases)		Segment Models: Low Social and Cultural, Low Pastoral Sports (154 cases)		Low Social, High Pastoral Sports (222 cases)		High Social, Low Pastoral Sports (225 cases)		High Social and Cultural, High Pastoral Sports (187 cases)	
Variable[a]	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value
ACHV	0.283	15.3	0.407	5.4	0.470	12.7	0.157	4.9	0.193	5.1
EXTR	0.102	5.3	0.249	4.1	0.010	0.3	0.129	3.6	0.133	3.5
PAST	0.061	3.5	-0.169	2.8	-0.0005	0.01	0.093	2.8	0.188	5.0
ATTR	0.249	17.9	0.372	9.2	0.373	12.5	0.196	8.3	0.280	6.6
AVAIL	-0.057	5.2	-0.133	4.0	-0.014	0.7	-0.035	1.7	-0.106	4.4
FEINC	-0.088	1.8	0.699	5.8	-0.062	0.8	-0.489	4.2	-0.131	1.0
DISTLDA	-0.0002	1.9	-0.0002	0.8	-0.0004	1.5	-0.023	1.3	-0.0005	1.8
CARLDA	0.041	1.8	-0.254	3.5	0.071	1.6	0.013	0.3	-0.085	1.6
GOLFAGE	0.008	4.1	0.023	4.3	0.014	4.3	0.006	1.1	-0.011	1.7
EDCULT	0.117	2.1	0.284	1.2	0.189	1.4	-0.176	2.3	0.286	2.0

[a] Alternative-specific constants have been excluded, for space considerations.

Table 5. T-tests of the differences in coefficient estimates for the attractiveness segments.

Segment	T-Values for Coefficient Differences: ACHV	EXTR	PAST	ATTR	AVAIL	FEINC	DISTLDA	CARLDA	GOLFAGE	EDCULT
1 and 2	0.75	3.21	2.44	0.03	2.98	5.65	0.51	3.84	1.40	0.35
1 and 3	3.08	1.68	3.82	3.76	2.46	7.13	0.11	3.21	2.29	1.90
1 and 4	2.56	1.62	5.06	1.57	0.66	4.56	0.81	1.89	4.07	0.01
2 and 3	6.38	2.15	1.93	4.66	0.73	2.68	0.48	0.95	1.35	2.28
2 and 4	5.24	2.17	3.70	1.80	2.83	0.29	0.31	2.23	3.47	0.48
3 and 4	0.73	0.06	1.89	1.72	2.19	1.99	0.81	1.44	2.00	2.78

ables produce coefficients that are significantly different between segments. The least distinction is found between groups 3 and 4, and the greatest differences are between groups 1 and 3 and groups 2 and 4. This suggests that the attractiveness of social-cultural activities gives the strongest segmentation, and the attractiveness of outdoor sports gives a rather poor segmentation.

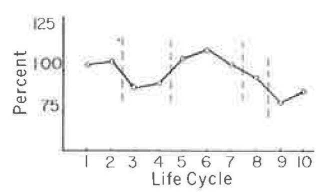
In conclusion, it may be stated that segmentation by attractiveness ratings has produced significantly different models, wherein most of the differences have intuitively meaningful interpretations.

Stage in the Family Life Cycle

The final segmentation variable used is a compound socioeconomic variable, which is given in the table below. It was felt that this compound variable would be a more useful segmentation variable than any of the simple socioeconomic variables considered in the preliminary work. For our purposes, married is interpreted as implying a household of two adults who live together. The compound variable has been found to be useful for travel-demand segmentation (14), as well as in other social science areas (23-25).

Stage	Definition
1	Young (≤35 years), unmarried, living alone
2	Young, unmarried, living with others
3	Young, married, no children
4	Married, oldest child <5 years
5	Married, oldest child between 5 and 12 years
6	Married, oldest child between 12 and 17 years
7	Married, oldest child over 17 years
8	Older (>35 years), married, no children at home
9	Older, unmarried, living alone
10	Older, unmarried, living with others

Figure 1. Percentage of mean participation versus life cycle.



One may suggest, a priori, how the life-cycle variable will affect recreation behavior. For example, people in stages 1 and 2 are likely to be more active because of a lack of various responsibilities and independence from other people; whereas in stages 3 and 4, which constitute a home-making stage, they would tend to be less active because of the existence of preschool children or because of the need for extra money, which leads to extra working hours and sacrifices from leisure time. A number of similar arguments can be advanced to suggest other groupings among life-cycle stages.

Because of some apparent similarities among some cycles and for pragmatic reasons, all 10 stages were not retained for population segmentation. It was therefore decided to group various stages to form segments. Initially, a graph was produced to show average activity-participation rates for each life-cycle stage. This is shown in Figure 1 and suggests that a reasonable grouping of stages would be (1, 2), (3, 4), (5, 6, 7), (8), and (9, 10). These are numbered as segment numbers 1, 2, 3, 4, and 5, respectively. Separate models were estimated for each segment by using these groupings and the same model specification as for the two previous segmentation procedures. The results of the segmented modeling are shown in Table 6.

The first test made on the segmented models is the likelihood-ratio test, which, after adjustment, produces a value of $-2 \log \lambda$ of 902 with 76 degrees of freedom. The table value of chi-square at 99.9 percent is approximately 112, from which one may again conclude that the segmented models perform significantly better than the unsegmented model. The results of t-tests of the coefficient differences among the five segments are shown in Table 7. All segments exhibit some significant differences from any other segment; the maximum number (7) was between segments 1 and 2 (stages 1 and 2 and stages 3 and 4), and the minimum(3) was between segments 4 and 5 (stage 8, and stages 9 and 10). Note, however, that segments 4 and 5 each contain very small samples, which has the effect of reducing significantly the reliability of the coefficients, so that only four have significant coefficients in both segments. This may,

Table 6. Models of life-cycle segments for Des Plaines and Evanston pooled data.

	Life Cycle 1 (125 cases)		Life Cycle 2 (189 cases)		Life Cycle 3 (324 cases)		Life Cycle 4 (57 cases)		Life Cycle 5 (90 cases)		Pooled (812 cases)	
Variable[a]	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value	Coefficient	t-Value
ACHV	0.315	6.0	0.402	9.8	0.229	7.5	0.593	5.7	0.398	5.1	0.283	15.3
EXTR	0.142	2.5	-0.123	2.9	0.192	6.5	0.298	2.0	0.361	4.7	0.102	5.3
PAST	0.073	1.6	0.002	0.1	0.144	5.4	0.845	6.1	0.167	2.2	0.061	3.5
ATTR	0.329	7.0	0.171	5.5	0.399	19.7	0.568	5.5	-0.230	4.3	0.249	17.9
AVAIL	0.035	1.1	-0.104	4.5	-0.084	5.0	0.162	2.0	0.011	0.3	-0.057	5.2
FEINC	-0.512	3.0	0.042	0.3	-0.373	4.2	-0.228	1.0	-0.646	2.8	-0.088	1.8
DISTLDA	-0.0009	1.9	0.001	3.6	-0.0003	2.4	0.0015	1.9	-0.0003	1.2	-0.0002	1.9
CARLDA	-0.243	3.8	0.103	1.5	0.026	0.8	-0.046	0.4	0.300	2.2	0.041	1.8
GOLFAGE	-0.023	1.3	0.033	1.8	0.014	3.8	0.067	4.2	0.0007	0.1	0.008	4.1
EDCULT	-0.138	1.1	0.108	0.6	-0.430	4.4	0.769	4.1	0.427	2.9	0.117	2.1

[a] Alternative-specific constants have been excluded, for space considerations.

Table 7. T-tests of the differences in coefficient estimates for the life-cycle segments.

	T-Values for Coefficient Differences									
Segment	ACHV	EXTR	PAST	ATTR	AVAIL	FEINC	DISTLDA	CARLDA	GOLFAGE	EDCULT
1 and 2	1.30	3.78	1.15	2.00	3.60	2.51	3.60	3.70	2.19	1.07
1 and 3	1.41	0.78	1.33	0.10	3.86	0.72	1.18	3.73	2.02	3.65
1 and 4	1.35	0.99	36.48	0.42	1.49	1.02	2.44	1.36	3.73	4.08
1 and 5	0.88	2.30	1.07	7.81	0.47	0.46	1.03	3.55	1.20	2.96
2 and 3	3.40	6.16	2.89	6.16	1.15	2.51	4.74	0.99	1.01	1.48
2 and 4	1.72	2.73	5.85	3.69	3.23	1.04	0.23	1.01	1.42	2.46
2 and 5	0.04	5.51	1.92	6.44	2.55	2.52	3.54	1.27	1.63	1.31
3 and 4	3.39	0.71	4.98	1.62	3.05	0.61	2.11	0.54	0.44	1.62
3 and 5	2.02	2.06	0.29	10.92	2.25	1.09	0.00	1.97	1.51	0.02
4 and 5	1.51	0.38	4.32	6.80	0.61	1.30	1.99	1.82	3.70	1.44

therefore, be the major cause of a lack of significant differences between coefficients.

The full interpretation of the differences among coefficient estimates is not given here because of space considerations; they can be found elsewhere (6). In summary, however, segmentation by life-cycle stages has revealed a significant number of plausible differences in the weights attached to the variables in the recreation-participation models. With the exception of two of the alternative-specific situational variables, all significant differences in weights point to expected differences in tastes and constraints. It seems appropriate to conclude, therefore, that this segmentation scheme is a worthwhile scheme that has identified a number of underlying differences in behavior, although the life-cycle variable may be operating as a proxy for a complex set of constraints and for personality maturation.

CONCLUSIONS

The results reported in this paper indicate that there exist significant variations in tastes and behavior that can and should be captured through population segmentation. Each of the tested segmentation schemes has revealed significant differences, and most of these differences bear plausible relationships to the segmentation variables. The use of a single, unsegmented model offers advantages of simplicity but will result in significant inaccuracies in the representation of recreation behavior, and may result in misdirected policies with respect to urban recreation facilities.

Separate prediction tests were not carried out, as this would have required reserving at least one-half of the already small sample for such tests. However, our experience is that the significant differences found in the models generally lead to poorer predictions if the unsegmented models are used in predictions.

It must also be noted that this research makes no claim to have identified optimum segmentation schemes. No attempts have been made to examine alternative groupings within segmentation schemes, to examine multiple segmentation (i.e., segmentation on more than one variable), or to seek optimal model specifications within segments. Until such efforts are made, we can only conclude that segmentation will improve model accuracy and that the segmentation schemes reported here will at least provide some gains in both policy insights and model accuracy.

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REFERENCES

1. L. Gapay. National Parks Battle to Deal with Crowds but Seem to Be Losing. Wall Street Journal, Sept. 15, 1976, pp. 1, 18.
2. P. Stoler. Bumper to Bumper in the Wilderness. Time, July 4, 1977.
3. C. J. Cichetti, A. C. Fisher, and V. K. Smith. Economic Models and Planning Outdoor Recreation. Operations Research, Vol. 21, Sept. 1973, pp. 1104-1113.
4. M. Clawson and J. L. Knetsch. Economics of Outdoor Recreation. Johns Hopkins Press, Baltimore, 1966.
5. V. R. Desimone and A. Zierenberg. Transportation Strategies for Parks and Recreation. Journal of the Urban Planning and Development Division, Proc., ASCE, May 1978, pp. 7-19.
6. A. Anas and others. Urban Recreation. Division of Research Applied to National Needs, National Science Foundation, Final Draft Rept., Grant APR 76-19086, 1978.
7. P. L. Watson and P. R. Stopher. The Effect of Income on the Usage and Valuation of Transport Modes. Transportation Research Forum Proceedings, Vol. 15, No. 1, 1974, pp. 460-469.
8. J. J. Louviere, L. M. Ostresh, Jr., D. H. Henley, and R. J. Meyer. Travel-Demand Segmentation: Some Theoretical Considerations Related to Behavioral Modelling. In Behavioral Travel-Demand Models (P. R. Stopher and A. H. Meyburg, eds.), Lexington Books, D. C. Heath and Company, Lexington, MA, 1976, Chapter 14.
9. D. A. Hensher. Use and Application of Market Segmentation. In Behavioral Travel-Demand Models (P. R. Stopher and A. H. Meyburg, eds.), Lexington Books, D. C. Heath and Company, Lexington, MA, 1976, Chapter 15.
10. D. McFadden. Quantitative Methods for Analyzing Travel Behavior of Individuals: Some Recent Developments. In Behavioural Travel Modelling (D. A. Hensher and P. R. Stopher, eds.), Croom Helm Ltd., London, 1978, Chapter 13.
11. T. Domencich and D. McFadden. Urban Travel Demand: A Behavioral Analysis. North-Holland, Amsterdam, 1975.
12. P. R. Stopher and A. H. Meyburg. Survey Sampling and Multivariate Analysis for Social Scientists and Engineers. Lexington Books, D. C. Heath and Company, Lexington, MA, 1978.
13. D. McFadden, W. B. Tye, and K. Train. An Application of Diagnostic Tests for the Independence from Irrelevant Alternatives Property of the Multinomial Logit Model. TRB, Transportation Research Record 637, 1977, pp. 39-46.
14. E. Aldana, R. DeNeufville, and J. H. Stafford. Microanalysis of Urban Transportation Demand. HRB, Highway Research Record 446, 1973, pp. 1-11.
15. P. R. Stopher and A. H. Meyburg. The Effect of Social and Economic Variables on Choice of Travel Mode for the Work Trip. In Transportation and Traffic Theory (D. J. Buckley, ed.), A. H. and A. W. Reed, Sydney, 1974, pp. 685-713.
16. L. L. Lucero. Towards Improved Demographic Groupings in Disaggregate Behavioral Modelling of Travel Demand. Department of Civil Engineering, Northwestern Univ., M.S. Thesis, Aug. 1978.
17. J. C. Nunnally. Psychometric Theory. McGraw-Hill, New York, 1967.
18. F. S. Koppelman and J. Hauser. Effective Marketing Research: An Empirical Comparison of Techniques to Model Consumers Perceptions and Preferences. Paper presented at TRB meeting, Washington, DC, 1978.
19. J. N. Prashker. Development of a "Reliability of Travel Modes" Variable for Mode-Choice Models. Northwestern Univ., Evanston, IL, Ph.D. dissertation, 1977.
20. J.-M. Choffray and G. L. Lilien. Industrial Adoption of Solar Air Conditioning: Measurement Problems, Solutions and Marketing Implications. Alfred P. Sloan School of Management, Massachusetts Institute of Technology, Cambridge, Working Paper WP 894-76, 1976.
21. Y. Allaire. The Measurement of Heterogeneous Semantic Perceptual and Preference Structures. Massachusetts Institute of Technology, Cambridge, Ph.D. dissertation, 1973.

22. J. R. Hauser. A Normative Methodology for Predicting Consumer Response to Design Decisions: Issues, Models, Theory and Use. Massachusetts Institute of Technology, Cambridge, Ph.D. dissertation, 1975.
23. D. Wells and G. Gubar. Life Cycle Concept in Marketing Research. Journal of Marketing Research, Vol. 3, 1966, pp. 355-363.
24. G. Katona, E. L. Mueller, J. W. Schmiedeskamp, and J. A. Sonquist. Survey of Consumer Finances, 1966. Institute for Social Research, Univ. of Michigan, Ann Arbor, 1967.
25. J. B. Lansing and J. N. Morgan. Consumer Finances over the Life-Cycle. In Consumer Behavior (L. H. Clark, ed.), New York Univ. Press, New York, Vol. 2, 1955.

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Sampling Vehicle Kilometers of Travel

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This paper develops sampling procedures for estimating vehicle kilometers of travel on urban streets. It shows how simple and stratified random sampling techniques can be applied to estimate sample-size requirements for estimating freeway, arterial-collector, and local-street vehicle kilometers of travel. The paper also presents and provides ranges in the parameters associated with the variations in traffic volumes in space and time. These estimates are then used as part of a practical, operational procedure.

Reliable estimates of urban vehicle kilometers of travel are important for many transportation planning and policy purposes. They help assess the effectiveness of safety programs. They provide a basis for allocating highway-user revenues and establishing highway financing programs. They help validate urban transportation planning models and monitor urban travel growths. They provide a means to assess the effectiveness of transportation system management, air quality, and energy conservation programs.

More than 40 years of research on traffic volume characteristics and variations (1-3) has shown that:

1. Urban traffic follows daily and hourly variation patterns that are generally consistent and often predictable. Urban traffic patterns exhibit relatively little weekday and seasonal variation. The percentage of total traffic in any given period is approximately the same along any route.
2. The more counts at a given location, the greater is the reliability. Similarly, the heavier the traffic volumes at a particular location, the greater is the reliability of the estimated volume.
3. The distribution of counts throughout the day is more significant than the total time during which the traffic is counted. Therefore, the number of separate and independent observations is more important than the duration of each observation.
4. Five- to six-minute short-counts are entirely satisfactory where traffic is not light or unduly erratic.

BASIC CONCEPTS AND VARIABLES

The most reliable method for developing traffic volume and vehicle kilometer information is to count each section of roadway for each day throughout the entire year. Such a procedure is neither practical nor possible. Consequently, it is necessary to apply sampling procedures.

Sampling urban vehicle kilometers of travel involves (a) identification of the basic variables and how they relate, (b) quantification of them, (c) statistical application of them, and (d) development of simplified procedures for practical use. This last step involves applying observed ranges in parameters to various sampling formulas to simplify computational steps.

Traffic volumes on the urban street system vary by time and space. Where estimates of vehicle kilometers are involved, the length of roadway section becomes a third variable. A link is defined as a section of roadway that has a uniform traffic volume. Sampling of vehicle kilometers of travel thus involves the following three basic sources of variation or error:

1. The variation in traffic volumes from one link to another (this is defined as the spatial variation among the population of traffic counts),
2. The variation in volumes on any given link resulting from day-to-day changes in traffic flow (this is defined as the temporal variations in traffic counts), and
3. The variations in the lengths of links.

These variations exist for volumes along any urban road system. The three types of variations are essentially independent of each other with zero correlation. This results in the following formula for the first two sources of variations.

$$S_x^2 = S_1^2 + S_2^2 + S_{1,2}^2 \tag{1}$$

Since we assume that $S_{1,2}^2 = 0$

$$S_x^2 = S_1^2 + S_2^2 \tag{2}$$

where

S_1^2 = spatial variance,
S_2^2 = temporal variance,
$S_{1,2}^2$ = covariance of S_1 and S_2, and
S_x^2 = composite variance in the population of traffic volume counts at a given point in time.

Estimation of the vehicle kilometers of travel per link is somewhat analogous to estimation of the area of a rectangle with errors in both the length and width. The variance in the vehicle kilometers of travel per link re-