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An Empirical Analysis of Urban Activity Patterns

by Wilfred W. Recker, Michael G. McNally, and Gregory S. Root

INTRODUCTION

This paper presents an empirical framework to assess the relationships between activities, constraints, and the manner in which they are channeled into particular time-space paths through the analysis of daily travel/activity patterns. The use of activity patterns as a surrogate for travel behavior and travel patterns is consistent with the position that trip making can be better understood when trips and

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activities are linked and analyzed as a collection of individual actions and interactions (Chapin 1974; Heggie 1978; Hanson 1979; Jones et al. 1983; Kutter 1981). In this approach, travel behavior is defined on the basis of knowing how people allocate time and sequence activities—the time-geographic dimension of complex travel patterns (Hägerstrand 1973; Cullen and Godson 1975; Lenntorp 1976; Burns, 1979; Burnett and Hanson, 1979, 1982).

The framework proposed is a simplified alternative to recent algorithms that focus on the classification of travel behavior in the form of travel/activity patterns to identify "typical" patterns representative of a given population. The complexity of the transformation of pattern data into a classification format is avoided through the specification of salient spatial and temporal features that characterize the physical representation of patterns and are directly classifiable. This research is based on the detailed analysis of the relationships between descriptors that characterize activity pattern profiles and those that characterize both the effects of time and location upon social and economic activity, and the effect of household attribute profiles.

Several studies have dealt explicitly with pattern classification. Hanson and Hanson (1981) utilized five-week travel/activity diaries and specified daily patterns as N-dimensional vectors which were factor analyzed. The original variable loading most strongly in each factor was utilized as the response variable in multiple regression models. The Transport Studies Unit (TSU) at Oxford has completed perhaps the most comprehensive assessment of complex travel behavior to date (Jones et al. 1983). The specific classification approaches employed differ from the others reviewed in that formal classification of patterns per se was not attempted. Instead, a priori categorization by lifestyle led to the qualitative assessment of "prototypical" activity patterns and observed, aggregate activity time budgets. Both discriminant and cluster techniques were used to investigate the independence and stability of the resulting behavioral groupings. Herz (1982) provides an empirical assessment of the influence of environmental factors on daily behavior, using a priori categorizations to define population subgroups, and employing techniques similar to the TSU effort in drawing his conclusions.

Recker and his colleagues (Recker et al. 1980, 1983, 1985; Recker and Schuler 1982) have applied pattern recognition theory to the classification of activity patterns using the same data set as in the present study. Walsh-Hadamard transformations (Welchel and Guinn 1968) were applied to the time-slice activity type and distance vectors, which were cluster-analyzed in transform-space utilizing a k-means nonhierarchial algorithm, and interpreted after an inverse-transform of pattern centroids. Measures of urban form and socio-demographics were related to the representative patterns using discriminant analysis (Recker and Schuler 1982). The approach has been successfully applied in the estimation of energy restrictions on pattern execution (Recker et al. 1981).

Pas (1982, 1983) also identified representative activity patterns through a similar procedure basing pattern comparison on a hierarchical, stop-based measure of similarity. The method of principal coordinates (Gower 1966) was used to transform these measures into Euclidean distances, and the resultant mapping was cluster-analyzed using a hierarchical algorithm. Parametric maximum likelihood models were estimated to establish relationships between the resultant representative patterns and socio-demographic measures. Golob (1983) has developed a methodology that eliminates much of the complexity of data reduction that precedes the classification process. Correspondence analysis (Saporta 1983) with time-slice, categorized variables is used to produce a one- or two-dimensional scale by which the pattern data are quantified and directly input to a nonhierarchical cluster analysis.

SPECIFICATION OF PATTERN FEATURES

The analysis of activity patterns is a classification problem with a set of measurements defining travel and activity participation. The dimensionality of the measurement vector, in general, will be large and span information superfluous to efficient classification. Consequently, it is advantageous to reduce the complexity of the measurement vector while retaining as much of the information content as possible, a procedure accomplished in the sequential stages of pattern specification, feature extraction, and classification. The special case of a linear feature extractor is "feature selection," in which features selected are a subset of the measurement vector. Although this simplest of the linear feature extractors involves the most subjective judgment, it was selected for the analysis reported herein because of its potential ease of application as a planning tool. Alternative classification procedures such as those of Golob (1983), Pas (1983), and Recker et al. (1980, 1983), although potentially effective in segmenting populations by revealed complex travel behavior, require relatively complex methodologies. The proposed approach simplifies the classification procedure through the a priori selection of travel/activity pattern features whose values are empirically derived and directly utilized in a clustering analysis leading to pattern identification, evaluation, and interpretation. The approach is similar to that of Hanson and Hanson (1981) in that a range of discrete pattern characteristics are selected for use in classification; however, an alternative, simplified selection process is developed.

The pattern features selected focus explicitly on the time-geographic depiction of human movement (Hagerstrand 1973) as a continuous, piecewise smooth surface in the time-space continuum. As with the significantly more complex transformation technique of Recker et al. (1983), the selected features in this approach characterize the *path* through time and space, while Hanson and Hanson select characteristics which best describe the underlying travel *behavior*.

Since the features selected will form the basis for subsequent classification of activity patterns, a priori judgments regarding the relative power of the elements to discriminate between dissimilar activity patterns must be made. The heuristic algorithm applied to identify candidate indices involved generating a simple hypothetical activity pattern and selecting a single feature which characterizes the path. An attempt was then made to identify a second feature that, if perturbed,

TABLE 1

Specification of Activity Pattern Indices

1. NEX	Total number of trips
2. TDIST	Total travel distance
3. TDISTM	Mean travel distance
4. TLAP	Total length of nonhome path in $\Sigma_n(T_n^2 + S_n^{20.5})$ Euclidean space-time
5. TEXRATIO	Measure of trip chaining $\begin{cases} [A-(N-1)]/A & \text{for } A>1 \\ -1 & \text{for } A=1 \end{cases}$
6. AVG	Mean spatial range*
7. STD	Mean spatial deviation*
8. SKEW	Spatial skewness*
9. PEAK	Spatial peakedness*
10. AREA	Area under pattern path in two-dimensional space (time and distance from home)
11. TBAR	Temporal Centroid $(1/\text{AREA})\int(t)d(\text{AREA})$
12. TRATIO	Activity budget/travel budget
13. TNHRATIO	Nonhome activity budget/travel budget
14. TNHACTM	Mean nonhome activity duration

*Sampled at 96 15-minute intervals.

would produce a dissimilar activity pattern with the same value of the feature that had been selected originally. The second feature was added and the process repeated until no feature could be identified which would produce a dissimilar activity pattern that had, as a subset, the same values of the features previously selected. The process was repeated for several hypothetical patterns until a stable set of indices capable of classifying patterns emerged.

Activity patterns were classified on the basis of a set of indices empirically derived from these features. These indices were divided into two major categories: (1) those indices associated with the spatial aspects of the activity pattern and (2) those indices associated with the temporal aspects of the activity pattern. Spatial indices are either distance-based (e.g., total distance traveled, mean trip length) or directly related to the movement space of the individual (e.g., total area of the activity pattern, degree of trip chaining, mean range of the activity pattern). Temporal indices measure either the amount of time allocated to various components of an individual's activity pattern (e.g., time spent at nonhome activities, time spent traveling) or how these allocations are distributed over the entire day. These indices are defined in Table 1.

APPLICATION OF FEATURE SELECTION

The classification indices presented form the basis by which individuals are categorized according to their observed daily travel/activity behavior. Characterizing the salient aspects of paths through time-space, these measures effectively transform complex travel/activity patterns into a more efficient, high information, and reduced dimensionality pattern profile. These profiles serve as input to the actual classification algorithm which results in the identification of groups of individuals who exhibit relatively similar travel/activity behavior.

Data

The data used in this analysis are drawn primarily from the 1976 SCAG/CALTRANS Urban and Rural Travel Survey, a comprehensive home interview survey conducted in 7,902 households cluster samples from the six-county SCAG region (Davis 1976). The instrument was designed to elicit information relative to travel behavior and attitudes, incorporating psychographic, attitudinal, and probability choice questions on present and future transportation system policy alternatives, in addition to conventional socioeconomic questions and a daily travel diary. All household members five years of age and older completed a 24-hour travel diary recording all trips made, by all modes (including nonvehicular trips). The diary was used to record trip timing information, spatial location, activity type, and a range of additional information. Inhome activities were not recorded.

Of the total sample, sixteen percent were drawn from Orange County, California, residences, from which a 20 percent subsample was randomly selected, comprising 665 individuals in 249 households. This information was supplemented with a range of demographic and urban form characteristics corresponding to the 431 analysis zones of the Orange County, California, Multimodal Transportation Study (OCTC 1979). The origins and destinations of the 2,946 trips reported in the subsample were coded according to the corresponding MMTS zone.

The subsample, two-thirds of whom were licensed drivers, was comprised of almost identical proportions of male and female respondents. The average age of respondents was 21–24 years with over one-third falling into either the 25–34 or 35–44 age category. Approximately 35 percent of the persons were classified as children; the next largest category (32.5 percent) consisted of heads of household (identified as the primary wage earner). Another 24.7 percent were categorized as spouse of a head of household. Half of the sample (50.7 percent) were unemployed

TABLE 2
Sample Distributions of Trips and Activities

	Trips			Activities		
Number	Obs.	Pct.	Cum.	Obs.	Pct.	Cum.
1	0	0.0	0.0	226	34.0	34.0
2	230	34.6	34.6	161	24.2	58.2
3	54	8.1	42.7	111	16.7	74.9
4	141	21.2	63.9	66	9.9	84.8
5	60	9.0	72.9	32	4.8	89.6
6	70	10.5	83.4	19	2.9	92.5
7	25	3.8	87.2	22	3.3	95.8
8	23	3.5	90.7	8	1.2	97.0
9 +	62	9.3	100.0	19	3.0	100.0

Mean Number of Trips 4.4(s.d. = 2.7)
Mean Number of Activities 2.8(s.d. = 2.2)

TABLE 3
Distribution of Activities by Purpose

Activity type	Number of activities	Nonhome Percent	Total Percent
1. Work	371	20.2	12.6
2. Work Related	143	7.8	4.9
3. Education	265	14.5	9.0
4. Shopping	300	16.3	10.2
5. Social, Entertainment	224	12.2	7.6
6. Recreation	126	6.9	4.3
7. Other	406	22.1	13.8
	1,835	100.00	
8. Return Home	1,111		37.7
All Trips	2,946		100.0

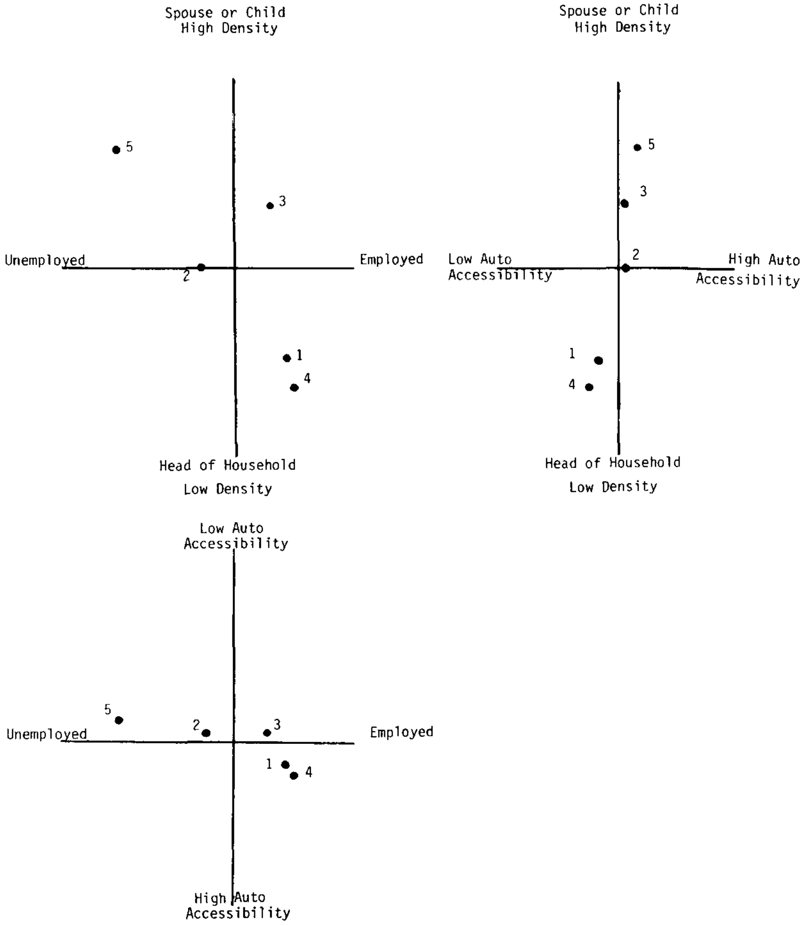
(here meaning not engaged in a compensatory occupation) as compared to 38.3 percent who were employed full-time. Over three-quarters of the heads of households were homeowners, with an average home value of $45,000–50,000. Approximately 85 percent of these homes were single-family dwelling units. The average rental value among renters was $200–250 per month. Average household income was approximately $19,000 per year but 40 percent had yearly incomes in excess of the average. The distribution of daily trips and activities is provided in Table 2, and a breakdown by activity type is provided in Table 3.

Classification Procedure

Indices were computed for the observed travel/activity patterns of the 665 individuals in the Orange County subsample and values were standardized to eliminate possible bias due to scale. The resultant pattern profiles were cluster analyzed using a k-means algorithm patterned after procedures developed by Ball and Hall (1967) and MacQueen (1967). Such an iterative partitioning approach was chosen over a hierarchical scheme since no implicit evolutionary development of pattern clusters was assumed to exist. Cluster initiation involved randomly selecting k profiles as initial cluster centroids. The algorithm minimizes the trace of the pooled within-group dispersion matrix, with Euclidean distance taken as the measure of similarity. Cluster centroids are recomputed at each pattern assignment with the process terminating when no solution can be improved by further reassignment. Additionally, if the activity-pattern generalization process is to be useful in transportation planning contexts, it must be possible to relate the various

TABLE 4
Discriminatory Variable Definitions

Socioeconomic Variables		
HHSTAT	=	Status of traveler with the household (1 = head, 2 = spouse of head, 3 = child, 4 = other)
SEX	=	Sex of traveler (0 = male, 1 = female)
LICENSE	=	Possession of valid driver's license (0 = no, 1 = yes)
EMPLMT	=	Employment status of traveler (0 = unemployed, 1 = employed part time, 2 = employed full time, 3 = employed full time + second job)
VEHPER	=	Number of vehicles per household member
Urban Form Variables		
DTPOP	=	Population density of zone of household residence
DREMP	=	Density of retail employment in zone of household residence
DTEMP	=	Density of total employment in zone of household residence
DHINCDU	=	Density of high income dwelling units in zone of household resident



representative index profiles generated by the process to observable characteristics of the travelers and the region in which the travel occurs. To demonstrate one approach in this regard, variables that describe the household traveler (e.g., auto ownership, household size, sex, income) together with those that describe the urban area (e.g., economic activity, land-use pattern) were used as discriminatory variables in a multiple discriminant analysis (Caculoos 1973; Lachenbruc 1975) of the index profiles (as determined by the classification analysis).

A total of 14 socioeconomic and 11 urban form characteristics were tested for significance in discriminating among the various index profiles. Of these, 9 were found to possess significant discriminatory power in at least one of the cases discussed below. These variables are described in Table 4.

RESULTS BASED ON CLASSIFICATION INDICES

While a comparison of psuedo *F*-ratios indicated that the respondents are best categorized into 4, or possibly 5, distinct groups according to pattern profiles, a brief description of broader classifications, provided in Table 5, better explains the development of these final groupings. Each classification analysis is characterized by a representative pattern profile, a comparison of profile centroids relative to derived discriminant functions, and summary of classification results.

Five-Group Cluster Results

The clustering results for the five-profile case are shown in Figure 1. The five profiles are characterized by distinct differences in activity pattern parameters. Profile 1 is associated with long travel distances to a fewer number of activities with relatively long durations. However, compared to the other profiles, a greater proportion of time is devoted to reaching nonhome activities. Activity patterns associated with profile 2 (the largest group) are characterized by a large number of efficiently organized short trips (i.e., chained trips) to activity sites of short duration. Profile 3 is comprised of activity patterns with travel of very short distances, earlier in the day, to one or a few activity sites with relatively long duration. The extreme negative value of the efficiency index, TEXRATIO, for this profile is caused primarily by values of -1 assigned to this index for "single-trip" activity patterns. Individuals with profile 4 exhibit characteristics similar to those associated with their counterparts exhibiting profile 1. Patterns of individuals with profile 5 are characterized by a small number of very short trips, made later in the day, to activity sites with short duration.

Results of a discriminant analysis of the five-profile case were relatively consistent with those or other cases considered, but with some significant differences in the

TABLE 5
Summary of Classification

No. of Representative Patterns	Pseudo *F*-Ratio	Discriminant Function 1	Discriminant Function 2	Discriminant Function 3	Classification Percentage Correct
2	243	EMP SEX NVEH DTEMP DPOP	N/A	N/A	70.0
3	238	EMP SEX NVEH	NHSTAT DPOP DTEMP	N/A	48.4
4	204	EMP	MHSTAT	"DENSITY"	47.7
5	221	EMP	MHSTAT	NVEH	38.3
6	207	—	not estimated	—	—
7	191	—	not estimated	—	—

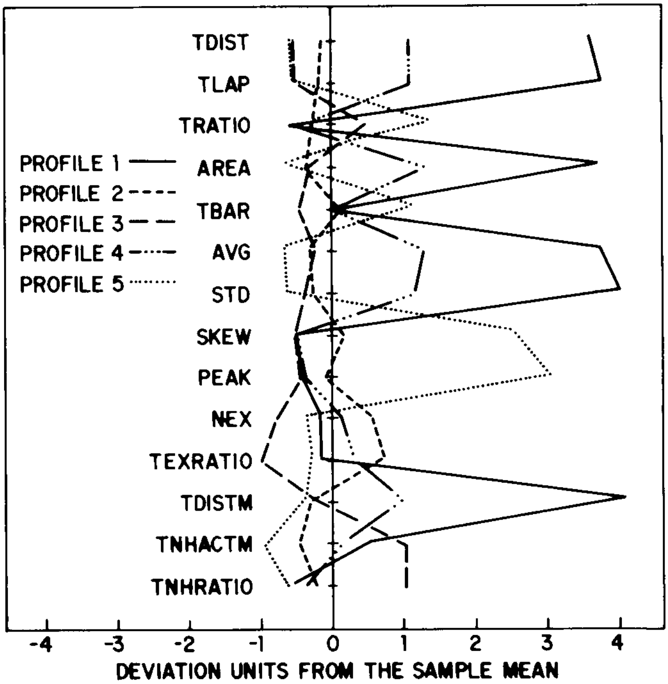


FIG. 1. Index Classification on the Basis of Five Groups

nonprincipal dimensions. Three discriminant functions were found to be significant discriminators of the five profiles. The first and most important of these functions was again dominated by the respondent's employment status. The second dimension, which in other analyses using fewer groups was influenced principally by the respondent's status in the household, is broadened to include elements of urban density, which in previous cases had been represented as a separate dimension. The third function is dominated by the number of vehicles per person in the respondent's household and represents a dimension which had not been found to be significant in any of the other cases. A summary of classification results is provided in Table 6.

Interpretation of Five-Group Cluster Results

Selected socioeconomic characteristics associated with the five-group clusters are displayed in Table 7 for each representative profile and for the sample as a whole. The analysis of socioeconomic profiles together with pattern profiles yields quite plausible interpretations of travel behavior.

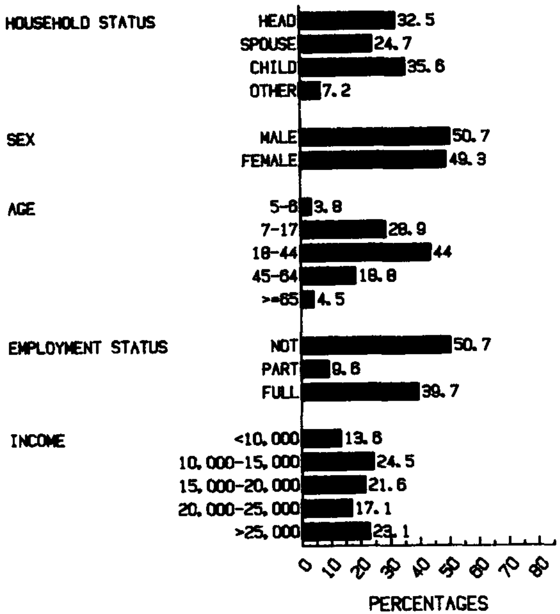
Group 1 is the smallest group, composed of 25 individuals. The most salient travel characteristic is total distance traveled, which at 77 miles is at least twice as great as any other group. An average of 3.5 trips are made, or one less than for the overall sample. A negative value of the efficiency ratio indicates a significant proportion of this group makes a single (presumably long) trip. Average nonhome activity duration is 4.3 hours.

The group is strongly characterized by employed (60 percent), high-income (70 percent of group at or over regional median) males (75 percent) between the ages of 18 and 44 (68 percent). Relative to urban form indicators, group 1 is strongly associated with low-density development. This group is very strongly correlated with group 4 relative to socioeconomic and urban form characteristics.

The largest cluster is group 2, comprising 302 pattern profiles (45 percent). These individuals perform the largest mean number of trips (5.8) and are also

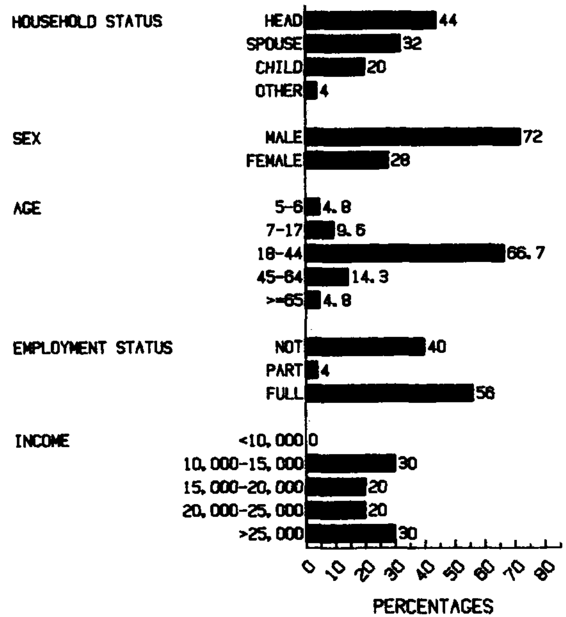
SOCIO-ECONOMIC PROFILES

FULL SAMPLE



SAMPLE SIZE = 665
MEAN HOUSEHOLD SIZE = 4.1
MEAN VEH/HOUSEHOLD = 2.3

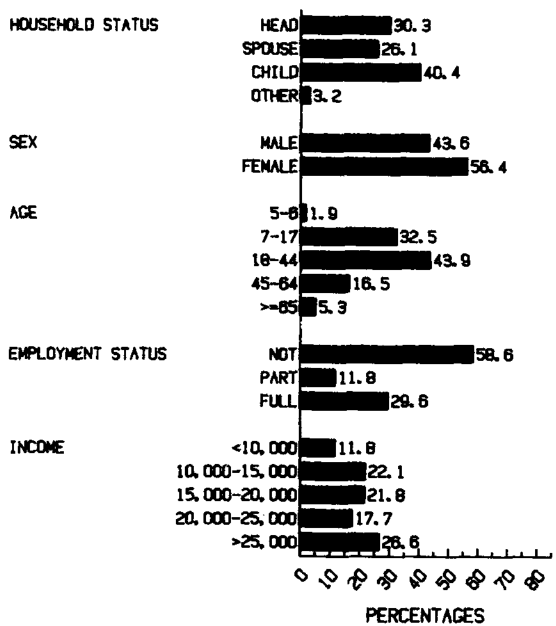
PROFILE 1



SAMPLE SIZE = 25
MEAN HOUSEHOLD SIZE = 3.8
MEAN VEH/HOUSEHOLD = 2.4

SOCIO-ECONOMIC PROFILES

PROFILE 2



SAMPLE SIZE = 302
MEAN HOUSEHOLD SIZE = 4.2
MEAN VEH/HOUSEHOLD = 2.2

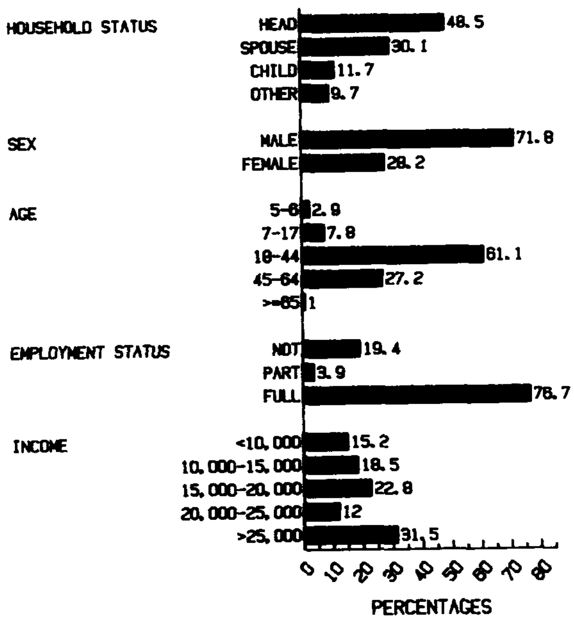
SOCIO-ECONOMIC PROFILES

PROFILE 3

SAMPLE SIZE = 178
MEAN HOUSEHOLD SIZE = 4.3
MEAN VEH/HOUSEHOLD = 2.3

SOCIO-ECONOMIC PROFILES

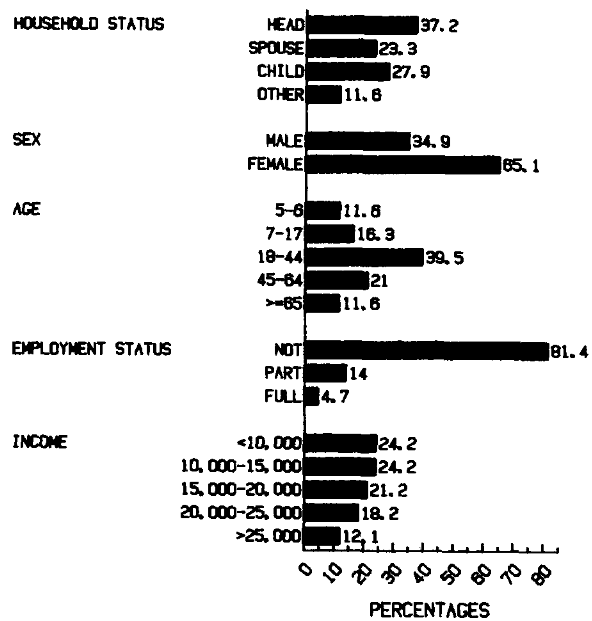
PROFILE 4



SAMPLE SIZE = 110
MEAN HOUSEHOLD SIZE = 3.8
MEAN VEH/HOUSEHOLD = 2.4

SOCIO-ECONOMIC PROFILES

PROFILE 5



SAMPLE SIZE = 48
MEAN HOUSEHOLD SIZE = 3.3
MEAN VEH/HOUSEHOLD = 2.2

TABLE 6
Classification Results for Five-group Case

Observed Group	Predicted Group (%) 1		2		3		4		5		*Observed Count*	*Observed Share*
1	6	(24.0)	1	(4.0)	3	(12.0)	13	(52.0)	2	(8.0)	25	(3.0)
2	36	(11.9)	93	(30.8)	65	(21.5)	43	(14.2)	65	(21.5)	302	(45.6)
3	23	(12.9)	32	(18.0)	80	(44.9)	25	(14.0)	18	(10.1)	178	(26.8)
4	35	(31.8)	10	(9.1)	9	(8.2)	50	(45.5)	6	(5.5)	100	(16.6)
5	9	(0.0)	11	(22.9)	12	(25.0)		(0.0)	25	(52.1)	48	(7.2)
Predicted Count	100		147		169		131		116		663*	
Predicted Share	(15.1)		(22.2)		(25.5)		(19.8)		(17.5)			
Proportion Predicted Successfully	6.0		63.3		47.3		38.2		21.6		38.3	

*Two observation discarded due to missing data.

characterized as having the highest travel efficient (0.63) indicating the travel patterns tend toward a large number of linked activities. Mean trip length is low (2.8 miles) as is mean nonhome activity duration (2.1 hours), both results being characteristic of patterns with linked activities.

Characterized by the predominance of individuals in the lower age brackets (over one-third less than 18, and 78 percent less than 45), this group contains a significant proportion of nonemployed individuals (less than 30 percent employed

TABLE 7
Socioeconomic Profiles

	Profile 1	2	3	4	5	Full Sample
Household Status						
Head	44.0%	30.3%	24.4%	48.5%	37.2%	32.5%
Spouse	32.0%	26.1%	18.3%	30.1%	23.3%	24.7%
Child	20.0%	40.0%	45.0%	11.7%	27.9%	35.6%
Other	4.0%	3.2%	12.2%	9.7%	11.6%	7.2%
Sex						
Male	72.0%	43.6%	51.7%	71.8%	34.9%	50.7%
Female	28.0%	56.4%	48.3%	28.2%	65.1%	49.3%
Age						
5–6	4.8%	1.9%	5.6%	2.9%	11.6%	3.8%
7–17	9.6%	32.5%	40.2%	7.8%	16.3%	28.9%
18–44	66.7%	43.9%	32.4%	61.1%	39.5%	44.0%
45–64	14.3%	16.5%	17.9%	27.2%	21.0%	18.8%
≥ 65	4.8%	5.3%	3.9%	1.0%	11.6%	4.5%
Employment Status						
Not	40.0%	58.6%	48.9%	19.4%	81.4%	50.7%
Part	4.0%	11.8%	8.9%	3.9%	14.0%	9.6%
Full	56.0%	29.6%	42.2%	76.7%	4.7%	39.7%
Income						
< $10,000	0.0%	11.8%	15.3%	15.2%	24.2%	13.6%
10,000–15,000	30.0%	22.1%	32.0%	18.5%	24.2%	24.5%
15,000–20,000	20.0%	21.8%	20.7%	22.8%	21.2%	21.6%
20,000–25,000	20.0%	17.7%	18.7%	12.0%	18.2%	17.1%
> 25,000	30.0%	26.6%	13.3%	31.5%	12.1%	23.1%
Sample Size	25	302	178	110	48	665
Mean HH Size	3.8	4.2	4.3	3.8	3.3	4.1
Mean VEH/HH	2.4	2.2	2.3	2.4	2.2	2.3

full-time). Discriminant results indicate that this group is closest to regional means on major discriminating dimensions.

The distinguishing attribute of the majority of the 178 (27 percent) individuals composing group 3 is a single, long-duration activity. The mean number of trips executed is 2.3 (2.1 trips fewer than the sample mean) and, together with the large negative efficiency ratio, indicates the preponderance of single-activity patterns. The mean activity duration of 6.9 hours is over 60 percent greater than for any other group. Group 3 is also characterized by the earliest time centroid, approximately corresponding to noon, and a spatial centroid of 1.5 miles from home.

An examination of the group's socioeconomic profile identifies the above travel characteristics as those typical of the two groups, full-time workers and school-aged children (each over 40 percent of the group). Household incomes are slightly less than the regional median, and mean household size is slightly greater. This group aligns itself with groups 1 and 4 on the employment discriminating dimension, but more closely with groups 2 and 5 with respect to measures of urban form.

The travel profile of group 4 (110 individuals) is quite similar to that of group 1, and the socioeconomic profile and measures of urban form are nearly identical. Total travel distance is substantially greater than the regional mean, but at 37 miles it is less than half of the corresponding index for group 1. Group 4 also makes an additional trip (4.5 mean trips), but has mean activity duration (4.3 hours) and time centroid (1:40 P.M.) similar to group 1.

The distribution of virtually all major socioeconomic characteristics are markedly similar (household status, age, gender, employment status) as are mean household size and mean vehicle ownership. The distribution of income is somewhat more uniform relative to group 1, with more lower-income households balanced by a larger proportion of higher-income households. Both groups weigh similarly on all discriminant axes.

The last of the representative profiles characterize the 48 individuals of group 5, overwhelmingly comprising nonemployed (82 percent) females (66 percent). This group is strongly identified with pattern centroids significantly different from those of other identified profiles. The time centroid is about 7:00 P.M., and the space centroid is one-eighth of a mile from home. Total travel distance and mean activity duration are (not surprisingly) the lowest in the sample, and the temporal ratios indicate a very small proportion of the day spent accessing or participating in nonhome activities.

The socioeconomic profile is characterized further by an older population (one-third over 45 years), and the smallest mean household size (3.3). In addition, 70 percent of the group is at or below regional median income. All three discriminant functions illustrate the polarity of this group relative to groups 1 and

TABLE 8
Selected Mean Profile Characteristics

	Pattern Feature	Representative Profile				
		1	2	3	4	5
Sample Size		25	302	178	110	48
NEX	Number of Trips	3.5	5.8	2.3	4.5	3.3
TDIST	Total Distance (mi.)	76.9	15.1	6.7	37.1	6.4
TNHACTM	Mean Nonhome Activity Duration (hrs.)	4.3	2.1	6.9	4.3	0.6
TEXRATIO	Travel Efficiency (see text)	− 0.2	0.6	− 0.8	0.2	− 0.2
TBAR	Time Centroid	2:12 P.M.	2:18 P.M.	11:55 A.M.	1:40 P.M.	7:06 P.M.
AUG	Distance Centroid (mi.)	13.4	1.3	1.5	6.6	0.0

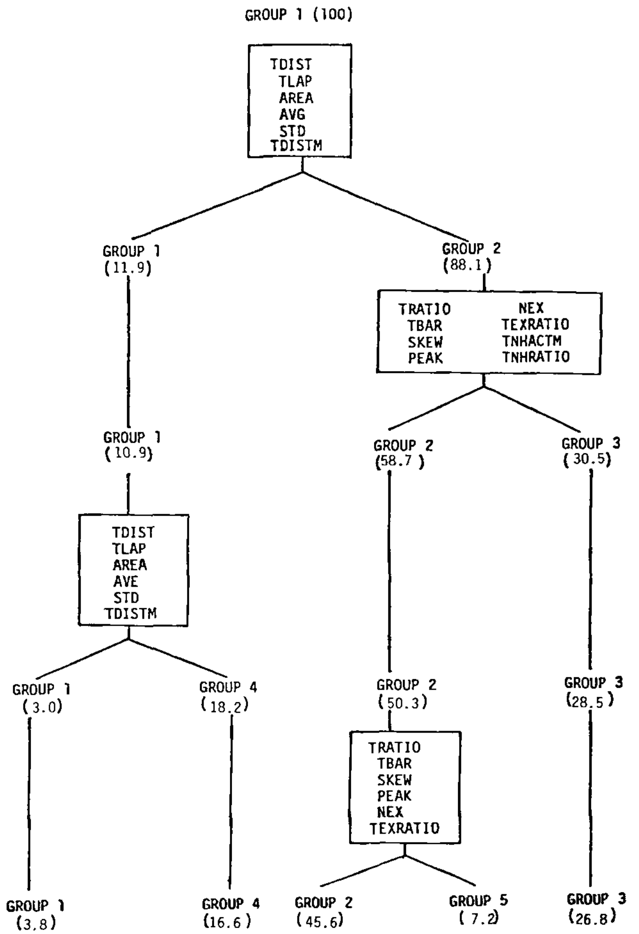


FIG. 2. Schematic Representation of Cluster Group Changes

4. Higher densities, lower auto accessibility, and lower labor-force participation are strongly identified with group 5.

In addition to the socioeconomic profiles provided in Table 7, a summary of selected travel characteristics is displayed in Table 8.

Evaluation of Profile Derivation

Although the clustering algorithm employed was nonhierarchical, it is useful to summarize the derivation of each profile to tree format. Figure 2 provides a schematic representation of cluster group changes, identifying principal travel/activity indices which serve to distinguish the profiles in addition to the percentage of the sample categorized into any particular group (indicated in parentheses).

COMPARISONS BETWEEN EXISTING METHODOLOGIES

The technique presented herein follows an overall approach inherent to virtually all existing travel/activity pattern classification algorithms, generally comprising five distinct subprocesses: (1) pattern specification, (2) data reduction, (3) pattern classification, (4) evaluation and interpretation, and (5) extensions to alternate classification characteristics. Each of the approaches reviewed in the Introduction of this paper utilize either conventional travel diaries or more comprehensive activity diaries, and have been applied to daily (or sequences of daily) travel-activity patterns. The pattern specification subprocess translates this information into a format for subsequent data reduction, and it is this latter stage where the algorithms differ the most.

The present approach is clearly the least complex and proceeds through the pattern analysis process using only standard techniques. Feature extraction involves only the simple calculation of selected indices; the measurements, after standardization, are input directly to the classification algorithm (in this case, a *k*-means, nonhierarchical approach). These results serve as direct input as response variables in multiple discriminant models. The approaches of Pas and of Recker and his colleagues involve significantly more complex comparison algorithms as well as an additional process step. Recker's rotational transform (Recker et al. 1983) must be inverted for interpretation, and the similarity measures of Pas (1983) must be translated via principal coordinates analysis. Golob's (1983) approach is less complex than the above. However, correspondence analysis is more complex than simple feature extraction and has not been widely applied in the transportation field.

The present analysis applies multiple discriminant analysis, utilizing the five identified pattern groupings as response variables, and successfully establishes relationships between revealed complex behavior and a range of traveler and environmental characteristics. The present results compare quite favorably with the rotational transform results of Recker which were drawn from the same data base. The range of selected features is quite limited along the activity dimension (only mean nonhome duration was used); thus, feature extraction was unable to distinguish between similar pattern profiles which differed only by the nature of the activity performed. An examination of the nine representative pattern results of Recker et al. (1985) with Pas's (1982) twelve-cluster results illustrates remarkably comparable results. Furthermore, the five-cluster results reported by Pas (1982) compare with the present results although, as with the transform results of Recker et al. (1985), the presence of lower-aged persons shifts the distribution of individuals associated with each representative pattern. Lastly, both approaches advanced by Recker et al. (1985 and present) incorporate explicit measures of distance traveled which proved significant in cluster identification.

SUMMARY AND CONCLUSIONS

Individual travel behavior has been analyzed as a collection of individual actions and interactions that lead to a sequence of activities and time allocations. These activity patterns have been evaluated empirically to assess the interrelationships between individual travel behavior and the location/intensity of economic activities in the environment. Distinct market segments based on similarities in travel/activity behavior were identified as well as the salient individual and urban form characteristics from which the activity patterns were derived.

Although the majority of activity-based approaches are intended for use as research tools, their potential worth is perhaps greatest in a planning and policy context. These methods allow for the estimation of impacts of alternate policies resulting from both direct effects (such as change in mode use and/or destination choice) and indirect effects (such as other household individuals gaining access to an automobile after another member's mode change). Recker et al. (1981) have illustrated the usefulness of a transformation approach to classification in estimating impacts of energy restrictions on travel behavior. The present state of the art in pattern classification suggests that these methods well may be the first application of activity-based models to gain widespread acceptance.

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