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Dynamic Tests of a Time-Space Model of Complex Travel Behavior

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1. APPROACH

The present approach to travel demand modeling postulates travel as a means of participating in activities away from home. The actual modeling effort concerns the formation of household activity patterns, with activity patterns being defined in terms of three dimensions: time, space, and category of activity. The activity dimension is in turn broken into two subcategories: on-site activities that take place over time at a single spatial location (e.g., working, shopping, or pursuing an activity at home), and travel, in which time is traded off for change of site location. Modes of transport are distinguished by different speeds and allow accessibility to different sites, depending on the spatial configurations of their networks.

The three-dimensional activity pattern conceptualization is depicted in two-dimensional space in Figure 1, which is an actual daily pattern observed in the data being used in the study. Time in this depiction is measured in ten-minute intervals (or time slices) along the x-axis, and a choice of 128 intervals from 5:30 AM to 2:50 AM is used in the study (where the number of slices is necessarily a power of two). Distance from home is recorded on the y-axis, the spatial dimension being compressed into this single dimension in the preliminary stages of model development. Finally, the category of activity is depicted as a label for each regime of the diagram. The manner of handling this nominal variable is through transformations described in the Analysis section.

The activity-pattern approach to travel behavior analysis is certainly not unique to the present research. A number of comprehensive overviews of works in the field of activity analysis are available and are not reiterated here.

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Previous analyses of activity patterns have generally been based on the creation of sets of numerical pattern indicator variables, generally called pattern "attributes." Such variables are meant to capture various pre-determined characteristics of daily or weekly activity patterns (or, in rare cases, patterns of longer time duration such as a month). Pattern attributes typically include the frequency of different activity sequences, time spent traveling by different modes, locations of activity sites (often in categories such as "in the home" and "in town"), and an enumeration of travel movements by time of day (usually hourly periods or periods such as "peak" or "morning").
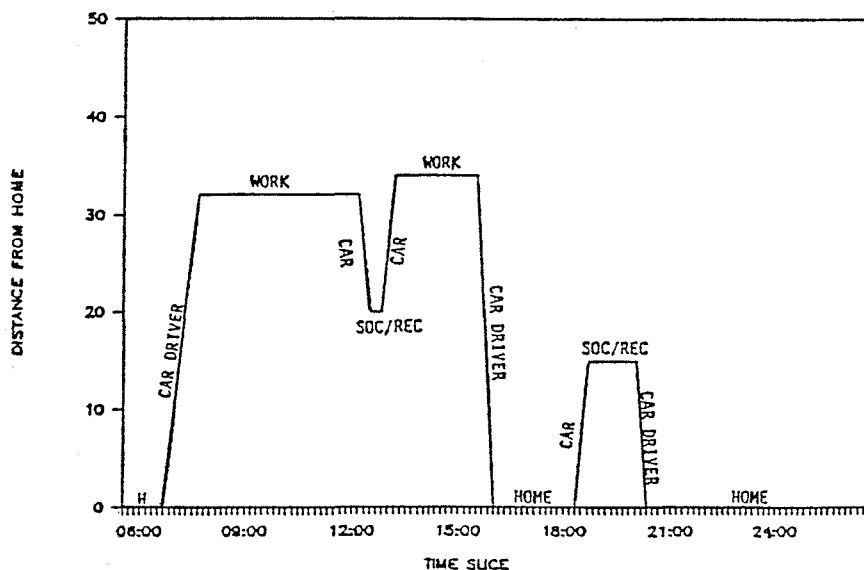
A DAILY ACTIVITY PATTERN FROM THE DATA
(PERSON # 1, HOUSEHOLD # 1037, DIARY DAY TUESDAY, MARCH 1984)

FIGURE 1

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The advantage of indicator variables is that they can be analyzed with conventional linear statistical methods, including discrete choice models for dichotomous variables, to relate patterns to characteristics of population segments. In fact, the search for "homogeneous" population groups on the basis of pattern indicators has been the primary objective of previous studies. The disadvantage is that interactions among the variables are generally lost, and such interactions are needed to capture the temporal and spatial connectivity of separate activities. The focus is on rates of occurrence of activities rather than on activity schedules and spatial paths.

As an alternative to indicator variables, it is useful to treat activity participation, and spatial locations of the activity sites visited as a time series, the series being measured along time slices of a day or of a longer period. There have been only limited applications of time-series analysis in the field of travel demand analysis (e.g., Herz, 1983), but recent methodological advances in time series analysis of nominal (categorical) variables (Deville and Saporta, 1983; DeLeeuw, 1984) have opened up the possibilities (e.g., DeLeeuw and Kreft, 1984).

In the research presented here, an attempt is made to analyze the entire daily activity pattern simultaneously in terms of its space, time, and activity category dimensions. The focus of the research is on developing procedures for the dynamic analysis of possible changes in activity patterns that may result from or lead to changes in the characteristics of the household. The intent is to trace the daily activity patterns of groups of travelers that have undergone significant change during multiple points in time, in a manner that will shed some light on both the nature and extent of associated changes in travel behavior. To check on the reliability of the

modeling process and to understand its peculiarities, complementary analyses of pattern attributes, and time-series analyses of patterns were performed on the same data set. Results from these complementary analyses are briefly outlined here, and it is hoped that these results aid in placing the present approach in the perspective of the rich legacy of previous work.

2. DATA

The data set being used is a subsample of the Dutch National Mobility Panel, which is described in Golob, et al. (1986), and Meurs and van Wissen (1987). A major advantage of using panel data is the ability to compare changes over time to cross-sectional differences and this is also pursued in the present study. The subsample encompasses the responses of all panel households residing in Amsterdam and the neighboring cities of Bussum and Purmerend for the first three waves of the panel (March 1984, September 1984, and March 1985). The subsample is special in that all trip destinations were geo-coded to the Dutch four-digit postcode level, a coding level that divides the city of Amsterdam into approximately 70 zones; the remainder of the Dutch panel has no spatial information available.

The geo-coded panel subsample consists of 378 separate households, 157 of which responded in all three waves of the panel. The panel is characterized by one-week travel diaries at each wave, and the 378 subsample households accounted for 17,470 trips to non-home (geo-coded) destinations. Further characteristics of the geo-coded panel subsample are provided in Golob and Recker (1987).

For the purposes of the research reported here, focus is on the 157 households in both waves one and three (1984 and 1985). These 157 households

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account for 4,480 daily activity patterns in waves one and three (320 persons over eleven years of age with 14 diary days per person). And as a first step in model development, focus is on the members of these households who were employed in both waves. There were 91 such individuals in the 157 households with full information on reported work hours per week and fixed versus variable work schedules. The dynamic breakdown of these employment variables is shown in Table 1. For demonstration purposes, preliminary research results are documented mainly for the segment of workers changing from fixed to variable work hours and for the corresponding segments with no changes in fixed or variable hours (all full time employed).

TABLE 1

DYNAMIC EMPLOYMENT SEGMENT SCHEME

Segment Number	1984 (Wave 1)		1985 (Wave 3)		Sample Size
	Full vs. Part Time	Fixed vs. Variable hrs.	Full vs. Part Time	Fixed vs. Variable hrs.	
1	Full	Fixed	Full	Fixed	35
2	Full	Variable	Full	Variable	26
3	Full	Fixed	Full	Variable	6
4	Full	Variable	Full	Fixed	7
5	Part	Fixed	Part	Fixed	7
(All other combinations)					(10)

3. ANALYSIS

Consider a set of instrumental, discrete variables $\underline{\alpha} = \left\{ \alpha_i \right\}$ that define the state of a household relative to its members' travel behavior. Such variables may include, for example, the household's level of automobile ownership, income, size, employment status, and income level. It is hypothesized that changes in $\underline{\alpha}$ will tend to impact the travel behavior exhibited by the household. Specifically, it is hypothesized that a change in state from $\underline{\alpha}$ to $\underline{\alpha}'$ will, under steady state conditions, be associated with a corresponding perturbation A to A' in the household's activity pattern. Such perturbations may be manifest in the scheduling of activities, their locations, the mode(s) used in accessing the activities, the number of activities performed and their relationship to other linkages in the household's collective activity pattern. These perturbations may precede the actual state change as the "stress" which precipitates the state change or may be a resultant of the state change.

The foregoing argument presupposes the existence of relatively stable and distinct sets of daily activity patterns associated with each definable state. That is, let

$$X_\alpha = \underset{i}{U} \; A_\alpha^i$$

denote the set of all daily activity patterns exhibited by households in state α, where A_α^i is the ith pattern manifest by households in α. Then

$$Y_{\alpha \alpha'} = X_\alpha \cap X_{\alpha'}$$

denotes the set of activity patterns common to households in states α and α', respectively, while

$$\overline{Y}_{\alpha \alpha'}; \mathscr{A} = \left\{ X_\alpha, X_{\alpha'} \right\}$$

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represents the set of activity patterns that are not shared by households in the α and α' states, respectively. Similarly,

$$W_{\alpha \ \alpha'} = X_\alpha - X_\alpha \cap X_{\alpha'}$$

represents the set of activity patterns exhibited by households in α and not by households in α'. For example, pattern attribute variables were computed for the daily activity patterns of the workers in each of the segments of Table 1 at two points in time (wave 1 in 1984 and wave 3 in 1985). These variables, which are numeric and can be analyzed with linear statistical methods, counted the number of home-based tours made by each of the five modes distinguished in this study, the number of tours with each combination of the four non-home activity category sequences, and travel times and distances per day and per tour.

A cross-sectional analysis was performed in which the pattern attributes of the full-time employed/fixed hours and full-time employed/variable hours segments (segments 1 and 2, Table 1) were compared using multivariate analysis of variance with repeated measurements design applied to the pooled wave 1 and wave 2 data (14 repeated days of observation). Seven pattern attributes were found to have significantly different means on the two segments and these are listed together with two other informative attributes in Table 2. Workers with variable hours make shorter and less complex home-based tours and make more tours using walking, public transport, and car driver modes, but less as car passengers than workers with fixed hours.

However, differences between the activity patterns of workers with fixed and variable hours might be explained by differences other than work schedules: the segments might differ in terms of socioeconomic characteristics (e.g., income, sex, household car ownership), relative

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TABLE 2

CROSS-SECTIONAL AND DYNAMIC ANALYSES OF PATTERN ATTRIBUTES FOR WORKERS WITH FIXED AND VARIABLE WORK HOUR SCHEDULES

ACTIVITY PATTERN ATTRIBUTE	Pooled 1984/85 Cross Sections		Workers Changing From Fixed to Variable Hours		
	Fixed Hours	Variable Hours	1984 Fixed	1985 Variable	Change (85–84)
2-link tours/day	1.09	1.28*	0.857	0.964	+0.107#
4 and 6+ link tours/day	0.127	0.120	0.143	0.036	−0.107#
Tours/day, main mode walking	0.268	0.355*	0.089	0.161	+0.071#
Tours/day, main mode public transport	0.124	0.179*	0.000	0.036	+0.036#
Tours/day, main mode car driver	0.646	0.834*	0.786	0.911	+0.125#
Tours/day, main mode car passenger	0.059	0.156*	0.036	0.036	0.000
Mean travel time/tour (min.)	59.7	51.9*	78.2	60.5	−2.53#
Total travel time/day (min.)	74.2	69.9	73.0	63.8	−9.3#
Tours/day, act 1: personal business; act 2: shopping	0.003	0.015	0.000	0.000	0.000

* Cross-sectional differences in means significant at $p = .05$ level according to repeated-measurements analysis-of-variance tests.

\# Longitudinal changes consistent with cross-sectional differences.

locations of home and work place, and many other factors. With panel data, it is possible to verify or reject cross-sectional relationships by focusing on persons who actually change values on the explanatory variable under study during the course of the survey. Changes in the pattern attributes for the segment of full-time workers changing from fixed to variable hours, 1984 to 1985, (segment 3, Table 1) are also shown in Table 2: seven of the nine attributes exhibited changes that were consistent with the cross-sectional differences while two of the attributes showed absolutely no change. This is an encouraging result in that it demonstrates the consistency of the panel data in light of relatively small sample sizes. The present research is oriented toward such an analyses of change rather than cross-sectional comparisons.

Under steady state conditions, it would be expected that the transition of a household from state α to α' would be accompanied by a corresponding replacement of the subset of activity patterns $W_{\alpha \alpha'}$ by $W_{\alpha' \alpha}$. For example, an indication of this effect is shown in Figure 2, which displays time series at two points in time of the proportion of person-weekdays that workers in segment (Table 1) are participating in activities away from home by ten-minute time slice. The curve with the higher proportion of away-from-home activities in the morning hours is for 1984 when the workers had fixed hour schedules; the curve with the higher peak in the evening hours is for 1985 when the workers had variable hours. There is a clear shift in activity scheduling that is not apparent in analyzing the static attributes of activity patterns (Table 2). The present approach attempts to capture both the nature of the activities and their scheduling simultaneously. Presumably, a positive test for:
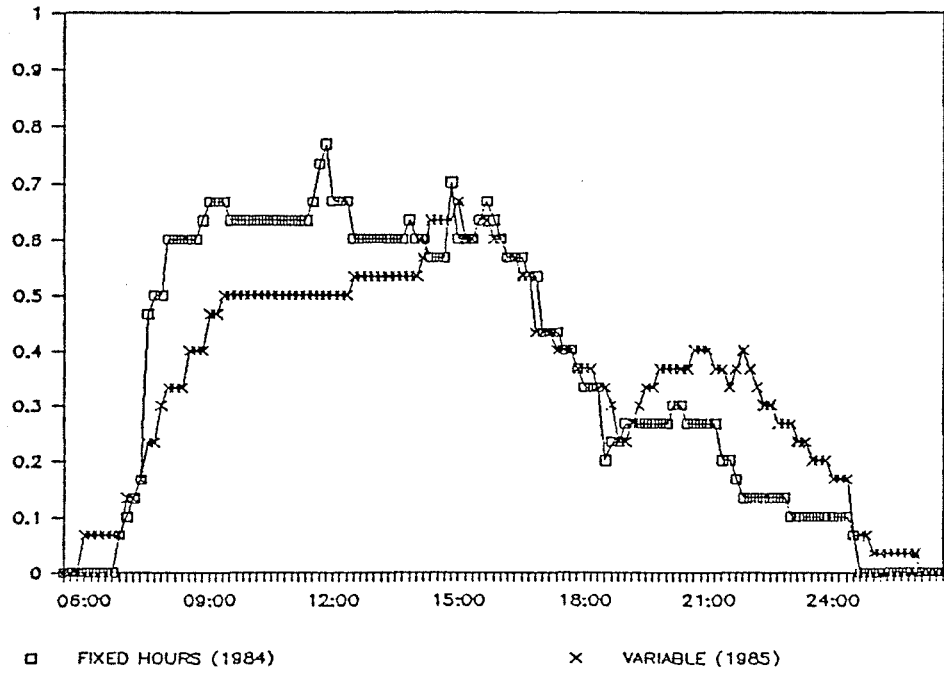
PROPORTION OF WEEKDAYS PERSONS AWAY FROM HOME
AS A FUNCTION OF THE TIME OF DAY

FIGURE 2

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$$W_{\alpha'\,\alpha} \subset X_{\alpha}^{\alpha'},$$

where $X_{\alpha}^{\alpha'} \subset X_{\alpha}$ denotes the set of activity patterns associated with households that transition to state α' during some time interval Δt (measured from t_0) required to reach steady state, would indicate that the desire or need to be involved in $W_{\alpha'\,\alpha}$ produced a stress which precipitated the state change $\alpha \rightarrow \alpha'$, while a negative test of this hypothesis (accompanied by a positive test at $t_1 = t_0 + \Delta t$) would tend to support the contention that the presence of $W_{\alpha'\,\alpha}$ at t_1 was a resultant of the state change $\alpha \rightarrow \alpha'$. Moreover, the relative size of $W_{\alpha'\,\alpha}$ can be considered an indicator of the impact of the state change on the daily travel behavior of the household.

Implementation of these concepts requires the ability to define, measure (or recognize), and compare the members (activity patterns) of X_{α} . These members are particularly complex in that they represent both temporal and spatial linkages of activities of many types by travel that may be described by many characteristics.

In this study, the temporal dimension of each activity pattern is divided into R grid points with each point i assigned values X [i, j; j = 1, . . . , Q] corresponding to the Q characteristics of the individual's activity participation at time i ; in this case, the individual's distance from home, a dichotomous indicator of travel, a set of five dichotomous indicators representing which activity is being performed, and a set of five dichotomous indicators representing use of a particular mode to access the activity, comprise the Q (Q = 12) characteristics of the pattern. Each daily pattern X is thus represented as an R x Q array containing, in

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this case, 128 x 12 = 1,536 bits of information. Although this representation is a convenient description of the daily activity pattern, the amount of information that must be processed precludes meaningful analysis of the complete activity pattern as an integrated entity. This obstacle can be overcome by decomposing the image into components based on an orthonormal set that spans the R x Q pattern space such that information content can be ordered by component.

The temporal variations of each of the twelve characteristic vectors used to describe the patterns were decomposed using a Walsh transformation (Whelchel and Guinn, 1968; Hadamard, 1893) based on binary functions (known as Walsh functions) which form a complete basis. These functions are defined as:

$$cal(i, \theta) = wal(2i, \theta)$$
$$sal(i, \theta) = wal(2i-1, \theta)$$
$$\left. \right\} \quad -1/2 \leq \theta < 1/2$$

$$wal(2i, \theta) = wal(2i-1, \theta) = 0, \qquad \theta < -1/2 \quad or \quad \theta \geq 1/2$$

where

$$wal(2k+q, \theta) = (-1)^{2k+1} wal(k, 2\theta + 1/2) + (-1)^{k+q} wal(k, 2\theta - 1/2)$$

with

$$w(0, \theta) = \begin{cases} 1, & -1/2 \leq \theta < 1/2 \\ 0, & \theta < 1/2, \theta \geq 1/2 \end{cases}$$

and

$$q = 0, 1 ;$$
$$k = 0, 1, 2, \ldots$$

The corresponding Walsh-Fourier series expansion of the jth characteristic of the pattern, $X(t, j)$, defined over $-1/2 < t \leq 1/2$ is

$$X(t,j) = a_{oj}\, wal(0,t) + \sum_{n=1}^{\infty} [a_{cj}(n)\, cal(n,t) + a_{sj}(n)\, sal(n,t)]$$

where

$$a_{oj} = \int_{-1/2}^{1/2} X(t,\ j)\ dt$$

$$a_{cj}(n) = \int_{-1/2}^{1/2} X(t,\ j)\ cal(n,t)\ dt$$

$$a_{sj}(n) = \int_{-1/2}^{1/2} X(t,\ j)\ sal(n,t)\ dt$$

The corresponding transformed pattern $Z\ (\ M \times Q\ )$ would have as components the first M coefficients a_{oj}, $a_{cj}(n)$, $a_{sj}(n)$. The advantage of this transformed representation is that it is possible to represent most of the information in the image by a relatively small number of Fourier components.

For discrete time slices, the transformation is generated from a Hadamard matrix (Hadamard, 1893) and is known as the Walsh/Hadamard transformation. The Hadamard matrix is a square array of plus and minus ones whose rows and columns are Walsh functions which are mutually orthogonal. The simplest Hadamard matrix is

$$H = \begin{Bmatrix} 1 & 1 \\ 1 & -1 \end{Bmatrix}$$

and any Hadamard matrix G of order 2N can be constructed from a Hadamard matrix H of order N by

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$$G = \begin{Bmatrix} H & H \\ H & -H \end{Bmatrix}$$

The Walsh/Hadamard transform of an $R \times Q$ image X is given by

$$Z = \frac{1}{R} H X$$

where R is restricted to 2^n. A unique feature of the Walsh/Hadamard transformation is that the original image can be reconstructed from the transformed image as

$$X = \frac{1}{R} H Z$$

The problem of determining the elements of X_α can then be relegated to that of determining the elements of

$$Z_\alpha = \bigcup_i Z_\alpha^i$$

where Z_α^i ($M \times Q$) represents the matrix of the first M coefficients of the Walsh Hadamard transformation of A_α^i. Subsequent inversion of the elements of Z_α produce the desired X_α.

The practical problem of determining the unique elements of Z_α can be addressed through application of a clustering algorithm. This problem has been simplified in transform space by clustering over the $M \times Q$ transform coefficients, rather than the $R \times Q$ pattern attributes. For example, in the current study the daily activity patterns exhibited by full-time workers who changed from having fixed working hours (α = fixed) in 1984 to having

flexible working hours (α' = flexible) in 1985, and vice versa (segments 3 and 4, Table 1) were transformed using the Walsh Hadamard transformation described above. The first ten transformation coefficients associated with each of the twelve pattern variables were retained and used in a k-means clustering algorithm to cluster similar transform coefficients for each of the patterns associated with the two situations analyzed. The "proper" number of groupings of similar transform patterns was determined on the basis of a pseudo F-ratio, and the R x Q transform coefficients associated with each of the groupings were averaged to obtain the set of unique elements of Z_α. These coefficients were subsequently inverted to produce approximations to the X_α.

This process invariably produces "fuzzy" images as the X_α. Since the transformed patterns that are grouped together are only similar, and not exactly alike, their group-averaged transform coefficients will, in general, produce activity pattern images which preserve neither the dichotomous nature of the activity/travel indicators, nor the consistency across all indicators required to ensure the integrity of the pattern.

The representative patterns that emerge from this analysis can at best be described in terms that are "fuzzier" than those used to describe the individual observed patterns. That is, the original sampling of position in the space/time/activity continuum may realistically have to be replaced with such qualitative terminology as "very complex" and "many tours." This latter fuzziness is characteristic of problems encountered in fuzzy set theory (Zadeh, 1965; Zimmermann, et al., 1984); the solutions to which involve the definition and application of membership functions to determine the degree of membership in any set, e.g., the set $W_{\alpha'}{}_\alpha$. In this manner, fuzzy set

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theory formalizes a mathematical definition of set membership that acknowledges ambiguity.

The segment of full-time employees who changed from fixed to variable work hours exhibited 34 and 36 "travel days" for Wave 1 and Wave 3, respectively. The resulting structure of the representative activity patterns (RAPs) for Wave 1 was simpler (5 RAPs) and of somewhat greater stability than for Wave 3 (8 RAPs). For each wave, approximately 75 percent of the patterns are categorized into two distinct patterns from which potential effects of the work hour change can be identified.

The RAPs for Waves 1 (1984) and 3 (1985) were ordered according to the number of travel days each represented, and the first two RAPs for each wave shown in Figures 3A through 3D. For Wave 1, the first RAP (Figure 3A) represents twelve of the 34 travel days. Although the activity distribution is complex, all trips were executed as car driver, and the temporal distribution of distance from home is consistent across all member patterns. The activity distribution is a blend of work and social-recreation activities mixed with in-home functions, with roughly 35, 25, and 40 percent, respectively, of the individuals participating in these activities at any time from 8:00 AM to 10:00 PM. Thirteen of the 34 patterns comprise an extremely well-defined second RAP (Figure 3B) characterized by a single, conventional "9 to 5" work activity (12 of 13 member patterns), accessed primarily by car driver mode. Travel times and distance were rather large, and there was no participation in evening out-of-home activities.

The transition from fixed to variable work hours is evident in the first RAP (Figure 3C) of the eight identified in Wave 3 patterns. This RAP 'C' comprises 19 travel days (14 weekdays) characterized primarily by work

□   Work
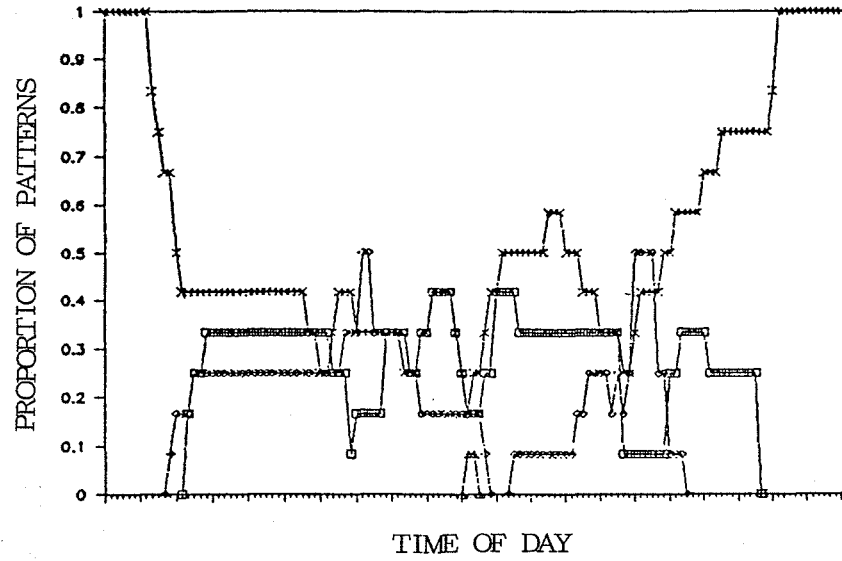
+   Shopping

◇   Soc.-Rec.

△   Pers.Bus.

×   Home

FIGURE 3A: WAVE 1, RAP 1

KEY

□   Work

+   Shopping

◇   Soc.-Rec.

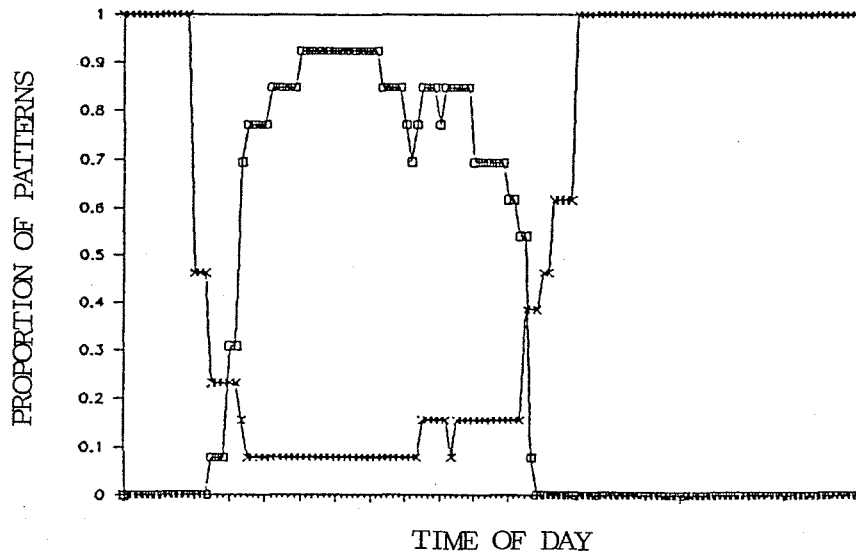△   Pers.Bus.

×   Home
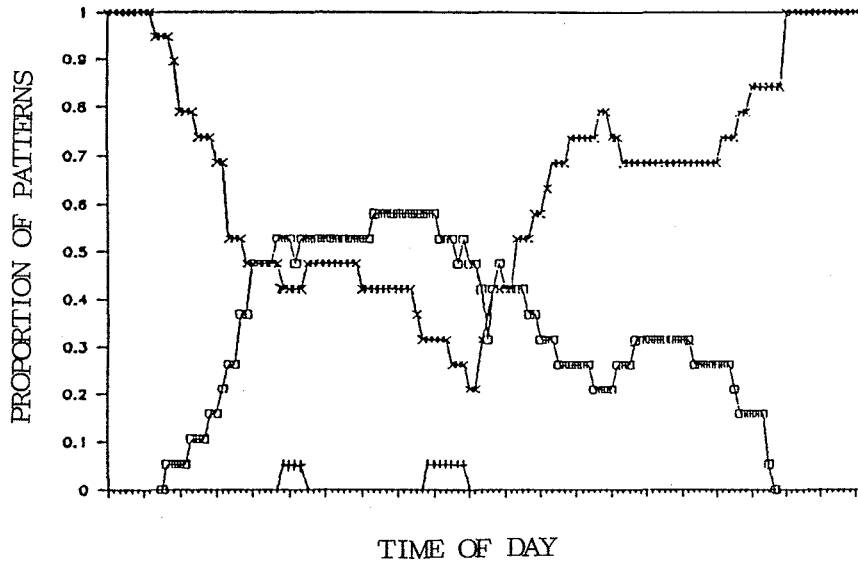

FIGURE 3B: WAVE 1, RAP 2

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FIGURE 3C: WAVE 3, RAP 1

KEY

□   Work

+   Shopping
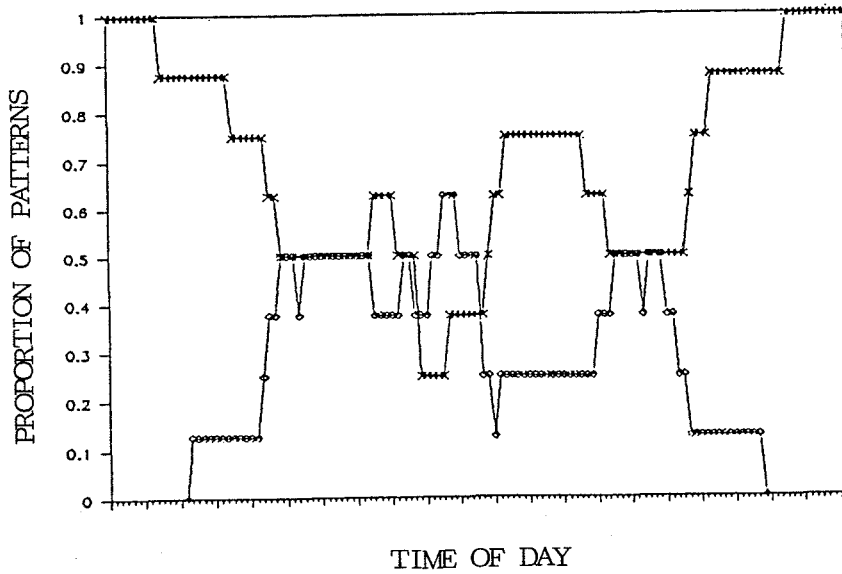
◇   Soc.-Rec.

△   Pers.Bus.

×   Home

FIGURE 3D: WAVE 3, RAP 2

FIGURE 3:   REPRESENTATIVE ACTIVITY PATTERNS

activities extending from 8:00 AM to midnight, with starting and ending times which are quite dispersed. The RAP primarily comprises patterns associated with individuals and travel days which constitute the first two RAPs of Wave 1. The Wave 1 work activities were characterized by rigid starting and ending times and significant distance in the case of the second RAP (Figure 3B). Although mode use remains constant (primarily car driver), the spatial distribution of activities reflects the increased temporal diversity of work participation, with a greater range of starting times. There is about a 0.50 probability of work participation before 5:00 PM, dropping to a 0.33 probability over the remainder of the evening. Virtually no other activities are evident. The second RAP of Wave 3 (Figure 3D) is similar to the RAP of Figure 3C, but with social-recreation activities replacing work activities. Half of the categorized patterns were weekend days, and some walking is identified.

The remainder of the RAPs in both waves represented only a few daily patterns, and were marked by extremes in pattern characters (either a diverse mix of activities and/or modes, or a significant proportion of the travel day spent at home or actually traveling). In further analyses, the association of such extreme RAPs with specific population segments can serve to identify specific travel demand markets and population groups with special travel needs.

The question of fuzziness has been addressed with elements of X_α characterized as a distribution of activity participation or travel. Changes indicative of work hour changes were evident in the pattern analysis, with increases in fuzziness accompanying flexibility in work schedules. Further research will focus on the effects on activity patterns of changes in factors such as car ownership, income, and life cycle.

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ACKNOWLEDGMENTS

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