the observed period of system overload and congestion, is likely to be different from that attached to corresponding time savings achievable under the conditions that this analysis suggests will prevail when a better balance between demand and system supply has been attained. This and other aspects of travel-time valuation are the subject of extended discussion elsewhere (6).

CONCLUSIONS

In the earlier sections of this paper, various aspects of the pattern of time-budget expenditure in Nigeria were examined. Engagement in supplementary employment was demonstrated to be an activity that has a significant effect on the allocation of time to the other activities recorded by survey respondents. In particular, engagement in this activity was shown to be associated with a reduction in daily travel time, especially that with respect to travel for purposes other than to or from work, and with greater variability in the time devoted to such travel.

The unusually high values of mean daily travel time recorded by Lagos and Ibadan residents, together with the explanations offered for the similarities and differences in travel-time variation in the two cities, in addition to that attributable to income and car-ownership effects, prompted the further exploration of possible relations between such variation and features of the local transportation system. It was concluded that, should the hypothesized relations between mean daily travel time and transportation system evolution be confirmed by other studies, they can be expected to have important implications for transportation modeling and time-valuation practice in Third World cities.

In the introduction to the final section of the paper it was noted that the ideas put forward are still somewhat tentative and require further elaboration. However, it is hoped that they will serve to stimulate further thought on the dynamics and implications of changes in the pattern of travel-time variation.

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Analytically Derived Classifications of Daily Travel-Activity Behavior: Description, Evaluation, and Interpretation

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One phase of a research study designed to enhance our understanding of urban travel behavior is discussed. In particular, this paper comprises the description, evaluation, and interpretation of analytically derived classifications of daily travel-activity behavior. A methodology that facilitates systematic identification of groups of similar travel-activity patterns is used to derive the typologies reported and examined here. This methodology is applied to a sample of 236 daily travel-activity patterns drawn from the Baltimore travel demand data set. Each of the sample observations is described by the set of stops made in a 24-h period; each stop is characterized by activity and time of day. The paper explores the hypothesis that a set of daily travel-activity patterns can usefully be described by its membership in a limited number of interpretable general classes. The results reported here show that the 236 daily patterns can be grouped into between 12 and 5 relatively homogeneous groups while retaining between 64 and 46 percent of the information in the data. The results also show that the

clusters may be interpreted by defining a small number of representative daily travel-activity patterns for each group. The analytically derived general classes of travel-activity behavior that are described and examined define a categorical response variable for use in models and analyses of daily urban travel behavior.

Recent research has begun to address two of the complexities of urban travel behavior; namely, that urban travel is a derived demand and that the elemental travel episodes (trips) over a day or week are not independent. The importance of accounting for these complexities in the understanding of urban travel behavior is well documented (1-5). The research reported in this paper is part of the ongoing effort to improve our understanding of urban travel behavior by recognizing and incorporating the above-mentioned complexities of the phenomenon in analyses and models. In particular, this paper reports the description, interpretation, and evaluation of classifications of individual daily urban travel-activity behavior. These classifications are derived analytically by applying a flexible and integrated methodology (5,6) to a sample of daily travel-activity patterns.

In order to analyze and model daily travel-activity patterns as complex entities, it is necessary to measure this behavioral phenomenon. Classification, which is a form of measurement, is employed in this research as well as in other recent efforts to examine and model complex travel-activity patterns (7-9, and paper by Kostyniuk and Kitamura elsewhere in this Record). Classification has also been employed by a number of travel-behavior researchers in the past. Some researchers have used a priori classifications (10,11), while others have classified travel behavior analytically (12-15). Because classification is the lowest form of measurement, an ability to classify is a necessary condition for analyzing and modeling daily travel-activity behavior as a complex entity.

In this paper, the hypothesis that a set of daily travel-activity patterns can usefully be described by its membership in a relatively small number of interpretable classes is examined. This hypothesis is based on the notion that general classes of daily travel-activity behavior can be identified because people with the same motivations and constraints relative to travel-activity behavior have similar daily patterns (5).

The remainder of this paper is structured as follows. First, the methodology is outlined briefly. Second, the data used in this research are described. Third, the cluster analysis results are reported. Fourth, two particular typologies of daily travel-activity behavior are evaluated and interpreted. Finally, the results reported here are discussed, and the analyses that have been undertaken by using the classifications described and evaluated in this paper are outlined.

METHODOLOGY

The classifications of daily urban travel-activity behavior reported in this paper are derived by using a flexible and integrated methodology (5,6). Briefly, the methodology comprises three stages (see Figure 1), which consist of a total of five interrelated steps that allow the systematic identification of classes of similar daily travel-activity behavior, as well as facilitating the interpretation and evaluation of these groups. In the first stage of the approach, raw input data that describe the 24-h travel-activity behavior of a sample of individuals are transformed into a configuration of points in a real Euclidean space, where each point represents one of the daily patterns being analyzed. This transformation is achieved in three steps. First, a modified version of the Burnett and Hanson (16) extension of the Hagerstrandian time-geography model is used to describe each daily travel-activity pattern. Second, the patterns are compared analytically by using a similarity measure (5). Third, principal-coordinates analysis (17) is used to determine the real-space configuration that best preserves the interpattern relations captured by the similarity measure. Thus, the more similar a given pair of patterns, the closer they are in the multidimensional space. The real-space representation is used as input to the group formation stage, which produces a selected number of relatively homogeneous groups of daily travel-activity behavior by using a well-known cluster-analysis algorithm. In the interpretation and evaluation stage, one or more representative patterns are identified for each group to facilitate interpretation of the cluster-analysis results, and sum-of-squares measures are used to evaluate the derived classifications.

The results reported and evaluated here are derived by using the methodology outlined above. In particular, these results are based on a description of each daily travel-activity pattern as a set of stops, where each stop is characterized by the activity at the stop and the time of day the stop was made. The index of similarity between daily travel-activity patterns used in this research allows for differential weighting of the characteristics used to describe each stop (5). Because activity type is considered more important than time of day in differentiating daily travel-activity behavior, the results reported below are based on a similarity index (between travel-activity patterns), in which activity type is weighted more heavily than time of day.

DATA

The data used in this research were collected in the Baltimore metropolitan area in 1977 (18). The data were collected by home-interview surveys conducted in a total of 966 households and include household and individual sociodemographic information as well as travel-activity behavior data. The latter includes all movements greater than one block in length, by all modes, during a 28-h reporting period that extends from 12:00 midnight to 4:00 a.m. the following day. The information obtained for each movement includes purpose (activity) at the destination, mode of travel, time of departure and arrival, land use at the destination, and the origin and destination of the movement (in terms of census block, tract, and traffic analysis zone).

The results reported in this paper are based on a subsample drawn from the Baltimore data set. This sample consists of data that describe the daily travel-activity patterns of 236 people who are 16 years of age or older. Examination of the distributions of the number of stops per day and number of tours per day reveals that more than one-third of the daily patterns in this sample incorporate two or more tours, while the majority of individuals in this sample make more than one nonhome stop in 24 h (5).

The daily travel-activity patterns analyzed in this research are described by the activity at each stop and the time of day at which the stop is made. The Baltimore data set differentiates 21 activity types at the destination end of each movement. In identifying general classes of daily travel-activity behavior, it is unnecessary and probably undesirable to differentiate such a large number of activity types. Reichman (19) is one of the first researchers to introduce the concept of life-style in the travel-behavior literature. In this context, he

Figure 1. Overview of methodology.

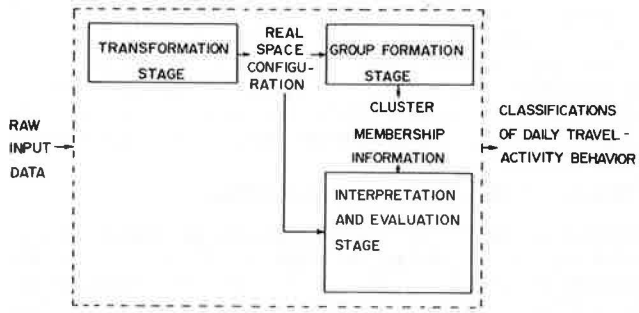
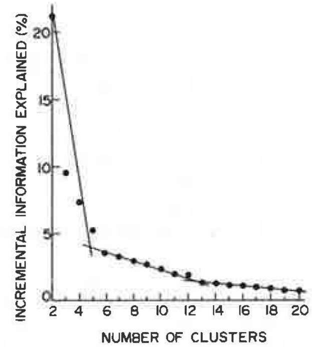


Figure 2. Incremental information explained as function of number of clusters.



suggests the grouping of out-of-home activities into three categories: subsistence (work, school), maintenance (shopping, personal business), and leisure. These categories, as well as return home, are selected for use in the research reported here. Five distinct time periods of the 24-h day are recognized in this research: early morning (4:00-7:00 a.m.), morning peak (7:00-9:30 a.m.), midday (9:30 a.m.-4:00 p.m.), afternoon peak (4:00-6:30 p.m.), and evening (6:30 p.m.-4:00 a.m.).

CLUSTER-ANALYSIS RESULTS

The output of the first stage of the methodology outlined above is a set of points in a real Euclidean space, where each point represents a daily travel-activity pattern. A real space of 32 dimensions is found to provide a good representation of the relations among the 236 daily patterns in this sample (5). This real-space configuration is used as input to the group formation stage. Ward's algorithm (20) is employed here to cluster the sample daily travel-activity patterns into a small number of relatively homogeneous groups.

Ward's algorithm is a cluster-analysis procedure in which objects and clusters are agglomerated hierarchically into nonoverlapping groups. Each step of the iterative procedure is guided by the objective of minimizing the within-group sum of squares, which is given by the following equation:

$$WSS_G = \sum_{g=1}^{G} \sum_{i=1}^{N_g} \sum_{\ell=1}^{L} (X_{i\ell g} - \bar{X}_{\ell g})^2 \quad (1)$$

where

WSS_G = within-group sum of squares for G groups,
$X_{i\ell g}$ = location on dimension ℓ of observation i of group g,
$\bar{X}_{\ell g}$ = mean location on dimension ℓ of observations in group g,
N_g = number of observations in group g,
G = number of groups, and
L = number of dimensions in the real-space configuration.

Because the total sum of squares is a constant for a given set of observations, minimizing the within-group (or error) sum of squares implicitly maximizes the between-group (or explained) sum of squares. That is, Ward's algorithm attempts to maximize the information (variance) accounted for by the classification of a large set of objects into a relatively small number of groups.

The cluster-analysis results are subjected to a preliminary examination in order to determine which cluster solutions should be interpreted and evaluated. This is accomplished by considering the incremental information accounted for by each unit increase in the number of clusters in the solution. This measure is defined as the reduction in the within-group sum of squares, which is expressed as a percentage of the total sum of squares, as follows:

$$\Delta I_G = [(WSS_{G-1} - WSS_G)/TSS] \cdot 100 \quad (2)$$

where

ΔI_G = incremental information explained by G clusters (relative to G-1 clusters),
WSS_G = within-group sum of squares for G clusters (see Equation 1),
WSS_{G-1} = within-group sum of squares for G-1 clusters, and
TSS = total sum of squares, i.e.,

$$TSS = \sum_{g=1}^{G} \sum_{i=1}^{N_g} \sum_{\ell=1}^{L} (X_{i\ell g})^2 \quad (3)$$

The incremental information explained by each additional cluster as a function of the number of clusters is shown in Figure 2 for 2 through 20 clusters. This diagram consists of three distinct segments. First, when the number of clusters is very small (<5), the amount of information explained is substantially increased by increasing the number of clusters, as expected. Second, there is an intermediate portion in which the incremental information due to an additional cluster is noticeable but not very large. Third, beyond 12 clusters the graph is very flat and is close to the horizontal axis, which indicates that each additional cluster accounts for only a very small incremental amount of information and that this increment is nearly constant with increasing dimensionality of the cluster solution. These data suggest that the 12 through 5 cluster solutions be examined in more detail. The results of such investigations are presented below.

INTERPRETATION AND EVALUATION OF CLUSTER-ANALYSIS RESULTS

The results of a cluster analysis have no inherent validity and should always be interpreted and evaluated (21). In this research, the cluster-analysis results are interpreted by identifying one or more representative patterns for each cluster in the solution. The need for such representative patterns and the rationale for the procedure used in their selection are discussed elsewhere (5,6). For each cluster, representatives are identified as those travel-activity patterns that are within some given distance of the cluster centroid. In particular, the patterns selected are those that satisfy the following relation:

$$d_{ig} \leq d_g + F\sigma_g \quad (4)$$

where

d_{ig} = distance between the centroid and the ith pattern of cluster g,
d_g = distance between the centroid and the closest pattern in cluster g,
σ_g = standard deviation of the distances between the patterns and centroid of cluster g, and
F = empirically determined parameter.

Equation 4 allows for the fact that some groups are very homogeneous and require few representative patterns, while other groups are relatively more heterogeneous and a number of representative patterns are needed for proper interpretation. Based on the results of exploratory analyses (5), the parameter F in Equation 4 is set equal to 0.10 to obtain the results reported here.

Ward's algorithm seeks to minimize the within-group sum of squares (see Equation 1). This measure is the sum of squares about the cluster centroids; therefore, the between-group sum of squares (the difference between the total and within-group sum of squares) may be thought of as the information explained by the cluster centroids. The between-group sum of squares is a useful measure of the information in the data set that is explained by the classification per se. However, it does not account for the fact that the representative patterns, which are used to interpret the classification results, do not capture all the information explained by the cluster centroids. The measure of information explained by the representative patterns is defined as follows:

$$I_G' = \left\{1 - \left[\sum_{g=1}^{G}\sum_{i=1}^{N_g}\sum_{\ell=1}^{L}(X_{i\ell g} - X_{\ell g}^*)^2\right]/TSS\right\} \cdot 100 \qquad (5)$$

where I_G' is the information explained by the representative patterns for the G cluster solution (percent), and $X_{\ell g}^*$ is the mean score on dimension ℓ of the representative patterns for cluster g, i.e.,

$$X_{\ell g}^* = (1/N_g') \sum_{r=1}^{N_g'} X_{r\ell g} \qquad (6)$$

where $X_{r\ell g}$ is the score on dimension ℓ of the rth representative pattern of group g, and N_g' is the number of representative patterns in group g.

The above formulation enables us to partition the total information in the data set into a number of components, because if N_g' in Equation 6 is set to equal to N_g (the number of patterns in cluster g), then $X_{\ell g}^*$ defines the centroid of cluster g and Equation 5 yields the percentage of information accounted for by the cluster centroids.

Figure 3 shows the breakdown of the total information for 12 through 5 cluster solutions into three components:

1. The information explained by the representative patterns for each cluster;
2. The incremental information due to the cluster centroids, relative to the representative patterns for each cluster; and
3. The information lost within clusters.

The results shown in Figure 3 confirm that, for a given set of travel-activity patterns, cluster solutions with fewer groups are less homogeneous, as expected. They also show that the information explained by the cluster centroids is considerable, even with a small number of clusters. For example, the 236 daily travel-activity patterns may be grouped into as few as six clusters while retaining almost 50 percent of the information in the similarity matrix. In general, the representative patterns do retain much of the information explained by the clusters. However, the representative patterns lose a significant proportion of the information accounted for by the cluster centroids when the set of patterns is grouped into a small number of clusters.

Interpretation of 12-Cluster Solution

Figure 4 shows the representative patterns identified by the criterion in Equation 4 for each of the groups in the 12-cluster solution. The representative pattern closest to the centroid of each cluster is also designated in this figure. The table below reports measures of the percentage of the information in each cluster that is accounted for by the cluster centroid and by the representative patterns:

	Information Explained (%)	
Cluster No.	By Cluster Centroid	By Representative Patterns
1	78.7	75.6
2	91.4	89.9
3	68.0	49.5
4	95.0	94.7
5	61.9	53.6
6	73.4	56.1
7	49.9	34.9
8	36.8	20.3
9	51.0	35.5
10	66.6	53.4
11	60.1	52.3
12	47.3	40.8
Total Sample	64.0	53.9

These measures are analogous to those defined earlier (Equation 5), except that the table reports cluster-specific measures. The overall measures are weighted averages of those for the individual clusters. The results reported in Figure 4 and the above table show that most clusters are relatively homogeneous. In 10 of the 12 clusters, the centroid accounts for 50 percent or more of the information in the cluster. Overall, the cluster centroids explain almost two-thirds of the information (64.0 percent) in the data. Also, for 6 of the 12 clusters, a single representative pattern accounts for 50 percent or more of the information in the cluster.

The pattern types in the 12-cluster solution are interpreted on the basis of the representative patterns depicted in Figure 4, and the results are reported in Table 1. Types 1 through 6 of this classification comprise a single nonhome stop. These groups differ in the activity at the nonhome stop and/or the time of day at which the stop is made. For example, types 1 and 2 both comprise a single stop for a maintenance activity, but they differ in terms of when the stop is made. Types 4 through 6 are single nonhome stop patterns for a subsistence activity and differ only in the time of day at which the stop is made.

Types 7 through 9 are daily travel-activity patterns comprising two nonhome stops made on two excursions from the home. Types 7 and 8 have a subsistence stop on the first out-of-home excursion, followed by either a leisure or maintenance stop, generally in the evening. Type 9 comprises two nonhome stops, both for a leisure activity. Pattern type 10 consists of multiple maintenance stops during the midday period. Types 11 and 12 are patterns comprising multiple nonhome stops made on numerous excursions from the home.

Interpretation of the Five-Cluster Solution

The interpretation and evaluation of the five-cluster solution, which uses the procedures described above, are reported here. The 5 clusters are found to be considerably more heterogeneous than the 12 clusters described above. The cluster centroids account for nearly half the information (45.6 percent) overall and for more than 40 percent of the information in four of the five clusters. However, a total of 26 representative patterns account for approximately 30 percent of the information in the similarity matrix (5).

The 26 representative patterns selected for the five-cluster solution provide the interpretations reported in Table 2. Pattern types 1, 2, and 5 each comprise a single nonhome stop. These pattern types differ in terms of the activity in which the individual participated as well as the time of day at which the nonhome stop is reached. Pattern types 1, 2, and 5 are maintenance, leisure, and subsistence-oriented patterns, respectively. Pattern type 3 consists of two or three nonhome stops made on two excursions from the home. The first nonhome stop is for a subsistence activity, and each pattern includes a maintenance and/or leisure stop. Pattern type 4 is an agglomeration of patterns of various forms, the common factor being that they contain numerous nonhome stops.

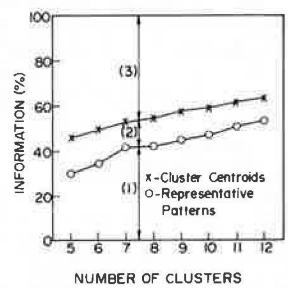
DISCUSSION OF RESULTS

The stability of the results reported above was examined by undertaking a parallel analysis that used a random hold-back sample of 223 observations. The results of the two analyses were found to be very similar (5). The interpretation of the identified classes of daily travel-activity behavior converged, but only at the five-cluster level. This is probably due to the relatively small samples employed in this research, and future research should explore the robustness of the classification results.

The results reported above verify the major hypothesis examined in this paper; namely, a set of daily travel-activity patterns may be grouped into a relatively small number of interpretable categories that account for a considerable proportion of the variance in the data. The results also show that the classes of daily travel-activity behavior may be interpreted by identifying one or more representative patterns for each distinct group of behavior. Finally, the results reported here show the analytically derived clusters to be intuitively acceptable.

The classifications of daily travel-activity behavior reported in this paper are intuitively acceptable. However, although it is difficult to choose between two different classifications of travel-activity behavior on an objective basis, the reader might subjectively prefer other 12- or 5-group classifications than those reported above. The virtue of the approach used to derive the results reported here is that it is objective in many respects, while subjective decisions are made explicit. For example, in defining a classification of travel-activity patterns, one might implicitly use a differential weighting of activity and time of day. In this research, such choices are made explicit.

Figure 3. Components of total information as function of number of clusters.



(1)-Information explained by representative patterns.
(2)-Incremental information explained by cluster centroids, relative to representative patterns.
(3)-Information lost within clusters.

Figure 4. Representative travel-activity patterns: 12-cluster solution.

GROUP NO.	REP. NO.[a]	ATTRIBUTE[b]	STOP NO. 1	2
1	1	ACTIVITY	M	H
		TIME	2	2
2	1	ACTIVITY	M	H
		TIME	4	4
3	1	ACTIVITY	L	H
		TIME	2	4
4	1	ACTIVITY	S	H
		TIME	1	3
5	1	ACTIVITY	S	H
		TIME	1	2
	2[c]	ACTIVITY	S	H
		TIME	5	3
	3	ACTIVITY	S	H
		TIME	5	2
6	1	ACTIVITY	S	H
		TIME	2	4

GROUP NO.	REP. NO.[a]	ATTRIBUTE[b]	STOP NO. 1	2	3	4
7	1	ACTIVITY	S	H	L	H
		TIME	1	3	4	4
	2[c]	ACTIVITY	S	H	L	H
		TIME	1	3	3	4
8	1[c]	ACTIVITY	S	H	M	H
		TIME	1	3	4	4
	2	ACTIVITY	S	H	M	H
		TIME	1	3	3	4
9	1	ACTIVITY	L	H	L	H
		TIME	2	2	2	2
	2[c]	ACTIVITY	M	H	L	H
		TIME	2	2	2	4
10	1	ACTIVITY	M	M	M	H
		TIME	2	2	2	2

GROUP NO.	REP. NO.[a]	ATTRIBUTE[b]	STOP NUMBER 1	2	3	4	5	6	7	8	9
11	1[c]	ACTIVITY	S	M	H	M	L	M	L	M	H
		TIME	2	2	2	2	2	3	3	4	4
	2	ACTIVITY	M	H	M	S	H	L	M	M	H
		TIME	1	1	2	2	2	2	2	2	2
	3	ACTIVITY	M	M	M	M	M	H	L	H	
		TIME	1	1	1	2	2	2	3	3	
12	1	ACTIVITY	S	H	M	H	S	H			
		TIME	2	2	3	3	3	4			
	2	ACTIVITY	S	H	S	H	S	H			
		TIME	2	2	2	3	4	4			
	3	ACTIVITY	S	H	M	H	S	L	H		
		TIME	2	2	2	2	3	4	4		
	4	ACTIVITY	S	H	S	H	S	H			
		TIME	1	2	2	2	3	3			
	5	ACTIVITY	L	H	S	S	M	S	M	S	H
		TIME	2	2	2	2	2	2	3	3	4
	6[c]	ACTIVITY	S	S	S	H	S	H			
		TIME	2	2	2	3	3	4			

a - representative pattern number

b - activity and time of day codes used in this table are as follows:

S - subsistence M - maintenance

L - leisure H - home

1 - morning peak 2 - midday period

3 - afternoon peak 4 - evening

5 - early morning

c - representative pattern closest to centroid

Table 1. Daily travel-activity pattern types: 12-cluster solution.

Type No.	Description	Proportion of Sample
1	Single nonhome stop patterns for a maintenance activity with movements in midday period	0.09
2	Similar to type 1 except that movements are in evening period	0.03
3	Single nonhome stop patterns for a leisure activity; non-peak-period movements	0.06
4	Single nonhome stop for subsistence activity; movements in morning and afternoon peak periods	0.13
5	Similar to type 4 except that movements are generally before the morning and afternoon peaks	0.08
6	Similar to type 5 except that movements take place after morning and afternoon peaks	0.10
7	Two nonhome stops separated by a return home after first stop; first stop is for a subsistence activity with peak-period movements; second nonhome stop is for a leisure activity with movements generally in evening period	0.07
8	Similar to type 7 except that second nonhome stop is for a maintenance activity	0.12
9	Two nonhome stop patterns with a return home after the first stop (as for types 7 and 8); both stops for leisure activity with movements mainly in midday period	0.06
10	Multiple maintenance stop patterns; all movements in midday period	0.08
11	Many out-of-home activities, generally including one stop for a subsistence activity; many maintenance stops with one or more leisure stops; at least two returns home during the 24-h period; movements in many time periods	0.09
12	Similar to type 11 except that these patterns contain at least two subsistence activities, and generally not more than one nonsubsistence activity	0.08

Table 2. Daily travel-activity pattern types: five-cluster solution.

Type No.	Description	Proportion of Sample
1	Single nonhome stop for maintenance activity; movements in midday period	0.14
2	Single nonhome stop for leisure activity; movements generally in evening	0.10
3	Two or three nonhome stops with the first for a subsistence activity; these stops take place on two forays from home; each pattern includes a maintenance and/or leisure stop; movements take place in peak periods, as well as in evening	0.20
4	"Long patterns", which consist of a large number of stops of all types and in all time periods	0.22
5	Single nonhome stop for subsistence activity; peak-period movements	0.34

This paper reports the results of an effort to classify daily travel-activity behavior analytically. Such classification is only a means to an end. The underlying objective is to explain and ultimately predict urban travel behavior. However, the classes of daily travel-activity behavior reported and examined above define a categorical variable. The latter may be used as a response variable in models and analyses of daily travel-activity behavior. The five-group classification reported in Table 2 has been used to examine relations between daily travel-activity behavior and selected sociodemographic characteristics (22). The latter are used as proxies for the role, life-style, and life-cycle attributes. These statistical analyses show that daily travel-activity behavior, which is characterized by general pattern classes, can be explained by particular characteristics of the individuals undertaking the different patterns. These analyses also isolate the specific differences in daily travel-activity behavior between people who have different roles and life-styles and who are at different stages in the life cycle.

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Travel-Time Budget: A Critique

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A critical evaluation of travel-budget concepts that stresses the travel-time budget is presented. Neither the detailed theoretical discussion nor the empirical findings from Baltimore and the Twin Cities of Minneapolis-St. Paul presented here support the concept of stability of travel-time budgets. The paper postulates some methodological improvements in travel-budget analyses that focus on the proper definition of the analysis unit. Making these improvements is seen as a prerequisite for finding meaningful regularities in travel behavior as well as for allowing comparisons of results. The alternative concept presented assumes stability of activity budgets (represented by trip rates) of homogeneous groups of persons. The proposed eight-category individual travel-demand model reveals many regularities in travel characteristics and satisfactory geographic transferability of trip rates of defined person categories.

Models that simulate social systems are often built around the assumption that certain properties of the phenomenon examined remain stable and constant for some period of time. In the past 20 years, the concept of the stability of travel expenditures of time and/or money has gained some popularity. Although this hypothesis, which is a tempting and attractive one, raises an interesting approach to the endeavor of transportation modeling, it thus far remains unproven. Recent opinions about the validity and applicability of travel budgets vary from cautious optimism (1-4) to skepticism (5-8) and leave some basic questions still unanswered.

Is the existing confusion caused by the variety of results obtained or, rather, the relative freedom of their interpretations? Is the methodology of this investigation correct? What is the proper analysis unit for travel-budget studies? Why is relative stability in very aggregated measures accompanied by high variability in disaggregated measures? Finally, is there an adequate theoretical base--and sufficient practical advantage--to support the replacement of the trip-rate concept by the expenditure-budget concepts in transportation modeling and forecasting?

In order to answer these questions, this paper attempts another critical and independent evaluation of travel-budget concepts. Four parts will be considered. First, an alternative look at previous findings is put forth. Second, a behavioral base and the importance of proper methodology for the travel-budget concept are discussed. Third, an empirical testing of travel-budget concepts for Baltimore (1977) and the Twin Cities of Minneapolis-St. Paul (1970) is explored. Finally, conclusions and recommendations are offered.

CONFLICTING EXPECTATIONS AND DIVERGENT FINDINGS

Variety of Concepts

Contrary to a clear and explicit concept of stability of trip rates, there is no uniform definition of a travel-expenditure budget. There are at least four formulations of the universal measure that are expected to remain stable:

1. Travel-time budget (1),
2. Travel-money budget (9),
3. Generalized expenditure budget (2), and
4. Household travel-distance budget (10).

Without going into details, one can easily note that these concepts are not necessarily compatible; if one is valid, another may not be. Sometimes two concepts can be compatible only under some special, but not very realistic, assumption (e.g., 1 and 4 are compatible only if speed v = constant).

Any specific travel-expenditure formulation can have a broad variety of definitions. For example, travel-money budget can be expressed as (a) total expenditure on transportation, (b) total expenditure on transportation as a fraction of total income, (c) total expenditure on transportation as a fraction of disposable income, and (d) current expenditure on transportation as a fraction of disposable income. As before, stability in one measure may automatically mean lack of stability in another. If many different measures are introduced, the chance is greater that one of them may show satisfactory consistency. Generally, the wide variety of concepts would not suggest that any specific travel-budget concept has a particularly strong theoretical background. Rather, attempts are made to support