BEHAVIORAL DYNAMICS IN ACTIVITY PARTICIPATION, TRAVEL, AND INFORMATION AND COMMUNICATIONS TECHNOLOGY

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CHAPTER NUMBER

BEHAVIORAL DYNAMICS IN ACTIVITY PARTICIPATION, TRAVEL, AND INFORMATION AND COMMUNICATIONS TECHNOLOGY

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INTRODUCTION

The unique event of the rapid advance and growing adoption and popularity of Information and Communications Technology (ICT) offers an unprecedented opportunity to study behavioral dynamics. This is unique for activity and travel behavior analysis because of the many claimed relationships between telecommunication and transportation. For example, using telecommunication as a source of information to reach locations and procure goods we can alter our traditional limitations of accessibility and virtually eliminate spatial separation. In addition, we may experience increases in schedule flexibility that may change our activity and travel patterns but may also alter our activity planning, location choice, and variety seeking behavior. On one hand, these developments may increase variability of activity and travel behavior and variability of travel demand potentially decreasing regularity and predictability. On the other hand, they also enable us to perform more interesting studies of travel behavior dynamics that may lead to better policy actions. These claimed substantial impacts of ICT motivate the need for research on the present and future impacts of telecommunication on activity and travel behavior by studying change of behavior. However, studying behavioral dynamics and change requires specific types of data such as panel survey data (i.e., repeated observation of essentially the same persons over time) and specific types of data analysis methods.

Using the Puget Sound Transportation Panel (PSTP) data, especially the data collected in Wave 7 (1997) and Wave 9 (2000), this study examines a variety of relationships between ICT and activity and travel behavior using a comprehensive conceptual model system that examines correlation patterns from both cross-sectional and longitudinal viewpoints. The data used are from two-day travel diaries of 1480 persons in 866 households that resided in the four-county region surrounding the Seattle metropolitan area.

Figure 1 shows the conceptual framework emerging from models developed in the past few years and used here to estimate a structural equations model. A plethora of relationships can be studied using this system. For example, the correlation among the amount of time allocated to in-home, out-of-home subsistence, out-of-home non-subsistence and travel, as well as the total number of activity episodes (in-home, out-of-home subsistence, out-of-home non-subsistence) can be estimated. The model system is designed to extend and parallel other past studies, and for this reason, variables at the household and person level are used. The information analyzed includes personal and household socio-demographics in the year 2000, changes in socio-demographics and ICT ownership and availability between the years 1997 and 2000, and the activity and travel behavior patterns in 1997. In addition, a new approach to account for the effects of state dependence in activity engagement and time use is proposed to test if behavioral habits of individuals still persist within the 3-year time interval. We first employ a pattern recognition technique known as latent class (LC) clustering analysis to identify relatively homogenous behavioral groups with observed activity engagement and time use variables in 1997. Then we use group membership indicators as explanatory variables in a structural equation model. This way also allows us to avoid serial correlation problems in panel data. In addition, some specific variables to the database in PSTP are also employed to account for other factors such as stratification sampling and potential self-selection bias. The model system depicted by Figure 1 is representative of the plethora of relationships that can be studied using it. For example, the correlation among the amount of time allocated to in-home, out-of-home subsistence, out-of-home non-subsistence and travel, as well as the total number of activity episodes (in-home, out-of-home subsistence, out-of-home non-subsistence) can be quantified and an estimate of possible substitution effects provided. The model system extends and parallels other past studies, and for this reason, variables at the household and person level that were used in past studies are used here too.

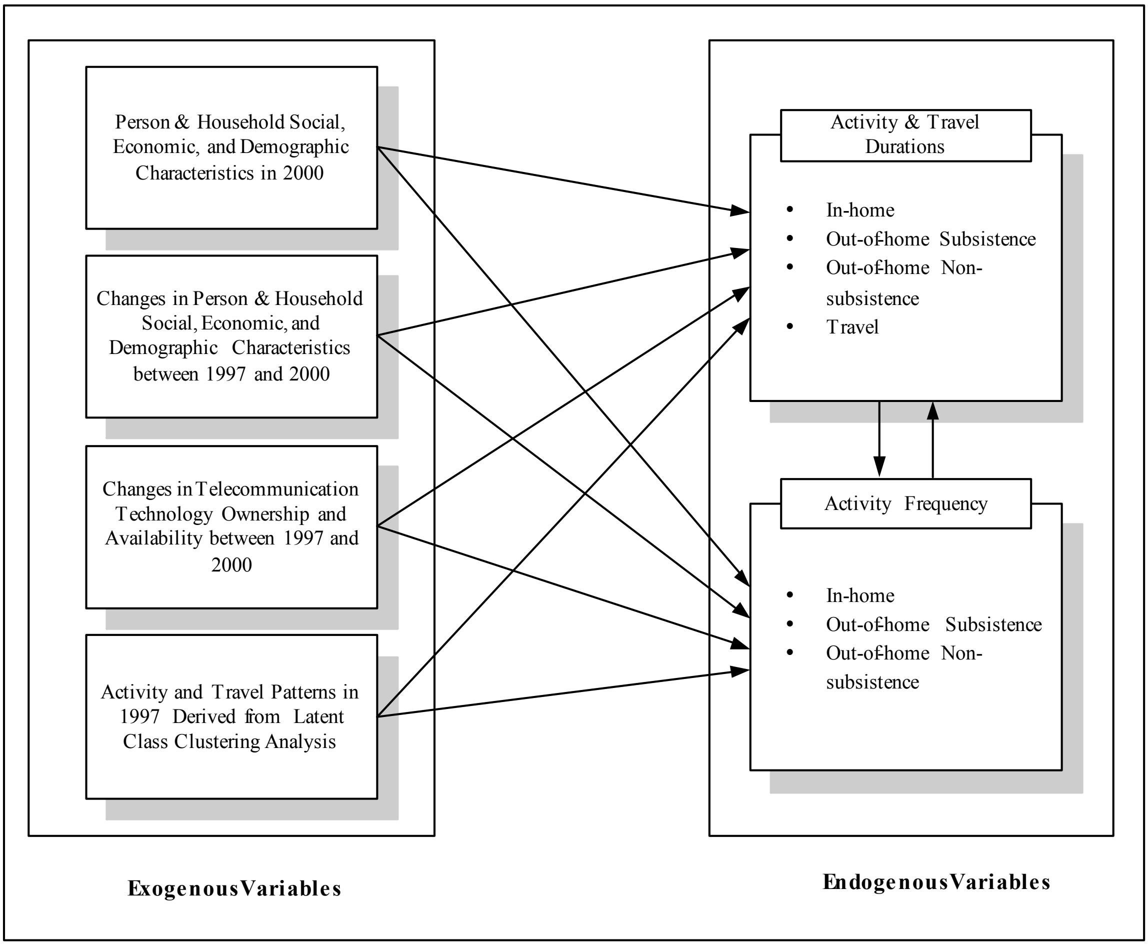

Figure 1 Conceptual Model

A formulation like this allows us to achieve several research objectives at the same time, such as:

- Identifying complex relationships among in-home and out-of home activities and travel in terms of time use and frequency of activity participation;
- Checking if there are systematic differences in time use and frequency of specific activities among population segments, while controlling for other exogenous variables;
- Examining whether or not there are symmetric effects of changes of person and household socio-demographics and ICT ownership and availability on the time use and frequency of specific activities ; and
- Developing a new technique to account for state dependence (past activity and travel behavior effects) in models that assess the effects of ICT on activity participation and travel.

A key aspect of this model system distinguishing it from other studies is the inclusion of "experience" variables. They are indicators of changes in the social and economic circumstances experienced by each respondent between 1997 and 2000 and they are included in the behaviour equations of the year 2000 as explanatory variables. The definition of these variables is such that allows to study behavioral symmetry when opposite events occur (addition of a vehicle versus subtraction of a vehicle from the household fleet). The second element that characterizes our research is the study of ICT on activity and travel behavior considered jointly with all the other determinants of travel behavior. Moreover, this research also develops a new method to account for state dependence effects in a time allocation model. Using activity engagement and time use indicators in 1997, homogenous groups are identified first through Latent Class cluster analysis and the group membership indicators are included as explanatory variables in the behavioural equations of the year 2000 to account for habit persistence. In the next section, a brief description of the data used is provided first, followed by model formulation and estimation results. The paper ends with summary and conclusions.

DATA USED

The Puget Sound Transportation Panel (PSTP) is the first and the only American general-purpose transportation urban household panel survey with data from Seattle and its surrounding four-counties in the United States (Murakami & Waterson, 1990). Unlike traditional cross-sectional transportation surveys, the PSTP is a panel or longitudinal survey in which similar measurements (i.e., surveys) are administered on the same households and their members repeatedly over time. Each survey occasion is called a wave and PSTP starting in the fall of 1989 continues until today with sample size of approximately 1700 households per wave with a total of ten waves.

Each survey collects three groups of data. They are household demographics, persons' social and economic information, and reported travel behavior through a household questionnaire and a two-day travel diary. In the travel diary, each household member who is age 15 years or older reports every trip made during two consecutive weekdays, which remained approximately the same throughout the panel years. Each trip is described by trip purpose, type, mode, starting and ending time, origin and destination, and distance. Based on the reported trips, out-of-home activity engagement information is derived from the trip purposes. The durations of activities are computed by the difference between the start time of the next trip and the end time of the current trip giving the sojourn time at an activity location.

In the original trip data of PSTP, the trip purpose for each trip has been classified into 9 different types at Wave 7 (work, school, college, shopping, personal business, appointment, visiting, free-time, and home) and 21 different types at Wave 9. The use of these different schemes for trip purposes between the waves makes it difficult to compare the two waves. To make the data for the two waves comparable and this analysis tractable, activity types have been grouped into:

- In-home
- Out-of-home Subsistence (work, school, and college), and
- Out-of-home Non-subsistence (shopping, personal business, appointment, errand/picking-up/dropping-off, free time, recreation/exercise, visiting, etc)

Since 1997, PSTP has included additional questions on respondents' traveler information system use and telecommunications and computer ownership to gain some insight on how people use traveler information to make their transportation decisions (Kilgren, 1998). This offered a unique opportunity to correlate ICT use with travel behaviour in a diachronic way. For the analysis in this study, we used the data from 1480 persons in 866 households who participated in both waves 7 and 9, and provided detailed information for all the variables used in this analysis.

Table 1 shows the number of persons, households, and a few social and demographic characteristics of the sample. It also shows a descriptive summary of key variables during the two interview days in wave 7 (1997) and wave 9 (2000). Activity duration is the total amount of time each person spends in a specific activity in a day. Total travel time is the total amount of time spent by a person traveling during the day. Therefore, the sum of activity durations for various activities and total travel time is equal to 1440 minutes per day for each person. Activity frequency is the number of activity episodes for each activity type each person engaged in a day. However, it should be noted that in this study all activities before the first trip and after the last trip are considered as one activity episode, because travel diaries do not provide information on activities before the first trip and after the last trip (usually at home). Therefore, the total number of trips is the sum of activity episodes minus one.

As expected, and as found in earlier studies (Ma and Goulias, 1997a, 1997b) using PSTP data, survey participants show more similarity in activity and travel patterns between the two days than between the two waves. The relatively large discrepancy between the two waves is most likely a result of genuine change but also the use of different coding schemes for trip purposes in the travel survey between the waves. However, it was found that there has been an increase in in-home activity and out-of-home non-subsistence activity durations between the waves but a decrease in out-of-home subsistence activity and travel. In terms of activity–travel, in the year 2000, the respondents spent an average of 1013.7 minutes in in-home activity, 239.0 minutes in out-of-home subsistence activity, 112.9 minutes in out-of-home non-subsistence activity, and 74.4 minutes in travel per day.

The bottom of Table 1 shows the characteristics of technology ownership and use in the sample with focus on the more modern technologies. Computer and Internet at home are the two fastest growing technologies and it shows there is a large proportion of the respondents who use computers in their daily lives. Computers at work appear to be stabilizing at 50% of the sample, and although Internet use at work is increasing, it did not reach the level of market penetration of computers at work. Cellular phone ownership is increasing even faster than computers and the Internet, causing a potential negative impact on pagers. Laptop computers and Personal Digital Assistants (PDA) are used by a small sample segment as reported.

Table 1 A Selection of Sample Characteristics

Characteristics			Wave 7 (1997)	Wave 9 (2000)
Number of persons in the sample			1480	1480
Number of households in the sample			866	866
Person & Household	Percent of males in the sample		46.9	46.9
	Number of employed persons in the sample		859	881
	Number of persons in household		2.5	2.5
	Number of cars per household		2.2	2.2
Activity & Travel Duration	Total amount of time in in-home activities (min.)	Day 1	965.2	1009.7
		Day 2	978.5	1017.7
	Total amount of time in out-of-home subsistence activities (min.)	Day 1	285.0	244.9
		Day 2	274.0	233.1
	Total amount of time in out-of-home non-subsistence activities (min.)	Day 1	104.9	110.4
		Day 2	108.2	115.4
	Total amount of time traveling (min.)	Day 1	84.9	75.0
		Day 2	79.4	73.8
Activity Frequency	Total number of trips per person	Day 1	4.57	4.08
		Day 2	4.30	3.98
	Number of in-home activity episodes	Day 1	2.43	2.26
		Day 2	2.36	2.23
	Number of out-of-home subsistence activity episodes	Day 1	0.98	0.81
		Day 2	0.93	0.81
	Number of out-of-home non-subsistence activities episodes	Day 1	2.15	2.01
		Day 2	2.01	1.93
Information & Communication Technology**	Number of persons who use computers regularly (%*)	At home	751 (50.7)	982 (66.4)
		At work	700 (47.3)	717 (48.4)
	Number of persons who use the Internet regularly (%*)	At home	458 (30.9)	896 (60.5)
		At work	438 (29.6)	544 (36.8)
	Number of persons having cellular phones (%*)		419 (28.3)	685 (46.3)
	Number of persons having pagers (%*)		156 (10.5)	129 (8.7)
	Number of persons having laptops (%*)		71 (4.8)	79 (5.3)
	Number of persons having PDAs (%*)		6 (0.4)	38 (2.6)

**** % over total number of person in the sample***

MODEL FORMULATION

Variables Used

Two groups of activity-travel variables are used as the endogenous variables in the SEM. The first group of the variables is total amount of time dedicated to a specific activity (in-home, out-of-home subsistence and out-of-home non-subsistence) and travel in a day. The second group is the number of activity episodes by the specific activity a person engaged in a day.

Table 2 Endogenous Variables

Endogenous Variables		Descriptions
Activity and Travel Durations	Hdur	Total in-home activity duration per day (min)
	Sdur	Total out-of-home subsistence activity duration per day (min)
	Nsdur	Total out-of-home non-subsistence activity duration per day (min)
	Ttime	Total travel time per day (min)
Number of Activity Episodes	Finhome	Number of in-home activity episodes per day
	Fsub	Number of out-of-home subsistence activity episodes per day
	Fnsub	Number of out-of-home non-subsistence activity episodes per day

For exogenous variables, five groups of variables were used: household-level variables, person-level variables, time-related variables, ICT variables, and previous activity participation pattern variables. Table 4 provides an inventory of all the exogenous variables used for this study. We used cross-sectional information in the year 2000, as well as longitudinal information between the years 1997 and 2000 about household-level and person-level social, economic, demographic characteristics and ICT ownership and availability. In addition, to take into account state dependence effects, we also used activity engagement and time use patterns in the year 1997 derived from latent class cluster analysis.

Table 3 Exogenous Variables Used in This Study

Household level	CARPOOL	Indicator, 1= household is sampled from carpool class; 0=otherwise
	TRANSIT	Indicator, 1= household is sampled from public transit class; 0=otherwise
	KITSAP	Indicator, 1= living in Kitsap County; 0=otherwise
	SNOHO	Indicator, 1= living in Snohomish County; 0=otherwise
	TOTADULT	Number of adults in the household who are 18 years old or older
	TOT6_17	Number of children in the household who are between 6 and 17 years old
	TOT1_5	Number of children in the household who are less than 6 years old
	MIDINC	Indicator, 1= $35,000 ≤ household income < $75,000; 0=otherwise
	HIGHINC	Indicator, 1= $75,000 ≤ household income; 0=otherwise
	MHINC	Indicator, 1= $35,000 ≤ household income; 0=otherwise
	DKINC	Indicator, 1=household income is unknown; 0=otherwise
	CAR2	Indicator, 1= two car household; 0=otherwise
	CAR3_	Indicator, 1= two car household; 0=otherwise
	INADULT	Indicator, 1=an increase in the number of adults in the household between waves; 0=otherwise
	DNADULT	Indicator, 1=a decrease in the number of adults in the household between waves; 0=otherwise
	INKID	Indicator, 1= an increase in the number of kids whose age is 6-17 in the household between waves; 0=otherwise
	DNKID	Indicator, 1= a decrease in the number of kids whose age is 6-17 in the household between waves; 0=otherwise
	INBABY	Indicator, 1=an increase in the number of children < 6 years in the household between waves; 0=otherwise
	DNBABY	Indicator, 1= a decrease in the number of children < 6 years in the household between waves; 0=otherwise
	INLICEN	Indicator, 1=an increase in the number of driver's license holders between waves; 0=otherwise
	DNLICEN	Indicator, 1=a decrease in the number of driver's license holders between waves; 0=otherwise
	INBPASS	Indicator, 1=an increase in bus pass holders in the household between waves; 0=otherwise
	DNBPASS	Indicator, 1=a decrease in bus pass holders in the household between waves; 0=otherwise
	INVEH	Indicator, 1=an increase in the number of cars in the household between waves; 0=otherwise
	DNVEH	Indicator, 1=a decrease in the number of cars in the household between waves; 0=otherwise
	INEMP	Indicator, 1=an increase in the number of employed persons in household between waves; 0=otherwise
	DNEMP	Indicator, 1=a decrease in the number of employed persons in household between waves; 0=otherwise
Person level	MALE	Indicator, 1=male; 0=female
	YOUNG	Indicator, 1=18≤ age ≤ 34; 0=otherwise
	MIDAGE	Indicator, 1=35≤ age ≤ 64; 0=otherwise
	PROF	Indicator, 1=having professional occupation; 0=otherwise
	MANAG	Indicator, 1=having managerial occupation; 0=otherwise
	SECRE	Indicator, 1=having secretarial occupation; 0=otherwise
	SALES	Indicator, 1=having sales occupation; 0=otherwise
	WK5	Indicator, 1=working outside of home for 5+ times a week; 0=otherwise
	DPUPIL	Indicator, 1= student; 0=otherwise
	DLICEN	Indicator, 1= having driver's license; 0=otherwise
	DBPASS	Indicator, 1= having bus pass; 0=otherwise
	EXPEMP	Indicator, 1= started getting employed outside home in both waves; 0=otherwise
	NOVEMP	Indicator, 1= employed outside home in wave 9 only; 0=otherwise
	QUITEMP	Indicator, 1= employed outside home in wave 7 but not in wave 9;0=otherwise
Time related	DAY2	Indicator, 1=the second day of diary; 0=otherwise
	TUE	Indicator, 1=diary on Tuesday; 0=otherwise
	WED	Indicator, 1=diary on Wednesday; 0=otherwise
	THU	Indicator, 1=diary on Thursday; 0=otherwise
	FRI	Indicator, 1=diary on Friday; 0=otherwise
Information and Communication Technology	EXPCW	Indicator, 1= using computers at work/school in both waves; 0=otherwise
	NOVCW	Indicator, 1= started using computers at work/school after wave 7; 0=otherwise
	QUITCW	Indicator, 1= stopped using computers at work/school after wave 7; 0=otherwise
	EXPNW	Indicator, 1= using Internet at work/school in both waves; 0=otherwise
	NOVNW	Indicator, 1= started using Internet at work/school after wave 7; 0=otherwise
	EXPCH	Indicator, 1= using computers at home in both waves; 0=otherwise
	NOVCH	Indicator, 1= started using computers at home after wave 7; 0=otherwise
	NOVNH	Indicator, 1= started using Internet at home after wave 7; 0=otherwise
	QUITNH	Indicator, 1= stopped using Internet at home after wave 7; 0=otherwise
	EXPCEL	Indicator, 1= using cellular phones in both waves; 0=otherwise
	NOVCEL	Indicator, 1= started using cellular phones after wave 7; 0=otherwise
	QUITCEL	Indicator, 1= stopped using cellular phones after wave 7; 0=otherwise
	EXPPAG	Indicator, 1= using pagers in both waves; 0=otherwise
	EXPLAP	Indicator, 1= using laptop computers in both waves; 0=otherwise
	NOVLAP	Indicator, 1= started using laptop computers after wave 7; 0=otherwise
	QUITLAP	Indicator, 1= stopped using laptop computers after wave 7; 0=otherwise
Previous Pattern	HBOUND	Indicator, 1= had home bound pattern in activity & travel behavior at wave 7; 0=otherwise
	WORKER_A	Indicator, 1= had worker_a pattern in activity & travel behavior at wave 7; 0=otherwise
	WORKER_B	Indicator, 1= had worker_b pattern in activity & travel behavior at wave 7; 0=otherwise
	WORKER_C	Indicator, 1= had worker_c pattern in activity & travel behavior at wave 7; 0=otherwise
	PWORK_A	Indicator, 1= had pwork_a pattern in activity & travel behavior at wave 7; 0=otherwise
	PWORK_B	Indicator, 1= had pwork_b pattern in activity & travel behavior at wave 7; 0=otherwise

To account for task allocation and roles within the household, number of adults, number of children by age group as well as vehicles owned and income representing resource availability are included as exogenous variables. In addition, in order to account for the sampling stratification of the panel participants, the county of residence and sample indicators (TRANSIT, CARPOOL) are also included as exogenous variables. Indicators for changes in household and person characteristics, such as increase or decrease in car-ownership, changes in household composition, and changes in employment, were used to examine the effect of the changes on time use and mode choice. Two types of time variables are also included. The first type is a diary day indicator to account for a correlation between the first and second diary day. The second type is the set of day of week indicators to account for different activity and travel behaviors among weekdays.

To examine the effect of changes in information and telecommunication technology between the years 1997 and 2000, we defined indicator variables for four groups of persons for each ICT:

- Persons that started using these technologies some time after 1997 and are using them in 2000 (*new users*);
- Persons that stopped using these technologies since 1997 (*past users*);
- Persons that never used them (*non users*); and
- Persons that started some time before 1997 and never stopped (*experienced users*).

We use structural equation modeling techniques here because they can estimate a set of simultaneous equations capturing the interrelationship among a large number of endogenous (the variables considered dependent variables in the system) and exogenous variables (the variables considered given to us outside the model system). This modeling technique is used in the analysis of travel behavior since the middle of the 1970's. A comprehensive and informative review of many transportation research applications using structural equation models (SEM) can be found in Golob (2003).

LONGITUDINAL ANALYSIS

Panel data enable us to measure change in a variable and concomitant effect(s) on another. From a behavioral viewpoint it is also interesting and useful to know if there is behavioral symmetry when the changes happen in opposite directions. For example, is the difference in activity participation the same when a person looses a job and how does that compare when a person gains a job? Or what is the effect of socio-demographic changes in the household (that is, an increase or a decrease in the number of children in the household)? This type of effects and relationships were hypothesized some time ago by Goodwin, Kitamura, and Meurs (1990), but they were not studied within a more comprehensive model system until the more recent analysis reported in Kim and Goulias (2004a, 2004b) and Kim (2004).

In this section, we first provide a series of descriptive statistics of changes taking place during the 3-year period 1997 to 2000 in PSTP. This is followed by a summary of findings from a SEM application that is described in more detail in Kim (2004).

Table 4 shows the average daily number of trips, travel time, and total activity participation for persons that entered the labor force between 1997 and 2000, persons that are no longer in the labor force in 2000 and the entire sample. The newly employed persons make more trips that the average but do not travel more and spend slightly more time in activities. Their variance (standard deviation for each indicator shown on Table 4) is higher for the number of trips and not for the travel time. For the persons that are no longer in the labor force in 2000 we see the opposite. They make less trips, stay for shorter time on the road, and have dramatically lower activity times. The associated variances are also much smaller indicating a lower propensity to heterogeneous behaviour.

Table 4 Year 2000 Average Activity and Travel Behaviour Characteristics of Persons Entering and Exiting the Labor Force

		Number of trips per day	Total travel time per day (minutes)	Total activity time per day (minutes)
Employed in Wave 9 but not in wave 7				
	Mean	4.61	70.03	368.43
	N	109	109	108
	Std. Deviation	3.63	61.89	267.33
Employed in wave 7 but not in wave 9				
	Mean	3.63	59.33	189.34
	N	512	512	509
	Std. Deviation	2.93	58.94	193.77
All the sample				
Total	Mean	4.08	74.97	376.89
	N	1480	1480	1473
	Std. Deviation	2.97	61.33	258.60

Table 5 shows another aspect of changes in demographics. Persons in households that have experienced an increase in the number of children ages 6 to 17 between the two waves have on average more trips per day and stay on the road longer. On the other hand their counterparts from households that experienced a decrease in the number of kids make on average 4.15 trips per day that is very close to the sample average of 4.08 trips per day. Similarly for their travel time. However, their total activity time is larger than the sample overall average and the average of persons in households that increased their children between the two waves.

Table 5 Year 2000 Average Activity and Travel Behaviour Characteristics of Persons Experiencing Increases and Decreases in the Number of Children at Home

		Number of trips per day	Total travel time per day (minutes)	Total activity time per day (minutes)
Increase in kids (ages 6 to 17) between waves				
	Mean	**5.33**	**84.52**	**475.29**
	N	**112**	**112**	**112**
	Std. Deviation	**3.37**	**50.33**	**217.90**
Decrease in kids (ages 6 to 17) between waves				
	Mean	**4.15**	**74.50**	**497.63**
	N	**169**	**169**	**168**
	Std. Deviation	**2.86**	**55.71**	**244.45**
All the sample together				
	Mean	**4.08**	**74.97**	**376.89**
	N	**1480**	**1480**	**1473**
	Std. Deviation	**2.97**	**61.33**	**258.60**

A third aspect we consider here is ICT ownership and use. Table 6 contains the average travel and activity characteristics for a day in the survey of wave 9 for persons in household that have either acquired internet in their households or stopped using internet in their households. Interestingly "new users" travel more and spend more time in activities. Their variance in activity participation, however, is lower than the persons that no longer have internet at home and than the overall sample.

Table 6 Year 2000 Average Activity and Travel Behaviour Characteristics of Persons that Started Using Internet at Home or Stopped Using Internet at Home

		Number of trips per day	Total travel time per day	Total activity time per day
Starting Using Internet at Home between 1997 and 2000				
	Mean	**4.65**	**84.26**	**500.46**
	N	**194**	**194**	**192**
	Std. Deviation	**2.89**	**56.95**	**213.09**
Stopped using Internet at Home between 1997 and 2000				
	Mean	**4.22**	**70.00**	**356.19**
	N	**88**	**88**	**88**
	Std. Deviation	**3.30**	**54.70**	**255.24**
All the sample together				
	Mean	**4.08**	**74.97**	**376.89**
	N	**1480**	**1480**	**1473**
	Std. Deviation	**2.97**	**61.33**	**258.60**

Tables 4, 5, and 6 provide a sample of the types of heterogeneous behaviour we attempt to capture when changes are taking place and we incorporate them into regression models that control for all other kinds of mutual influences among indicators of travel and activity behaviour. Using as guideline the model in Figure 1 and as explanatory variables the list of Table 3 a variety of models were estimated, tested, compared and one was selected as the master model from which to extract inferences. Before proceeding to the presentation of the findings we should mention that a SEM produces three type of effects of one variable on another: direct, indirect, and total effects. The overall model can be written as:

$$y = \mathrm{B}y + \Gamma x + \zeta \tag{1}$$

where $y = p \times 1$ vector of observed endogenous variables.
$x = q \times 1$ vector of observed exogenous variables.
$\mathrm{B} = p \times p$ matrix of coefficients of the y-variables.
$\Gamma = p \times q$ matrix of coefficients of the x-variables.
$\zeta = p \times 1$ vector of equation errors.

SEM is a covariance–based model, which means the differences between the sample covariances and the covariances predicted by the model are minimized. The underlying theory of this estimation procedure is that the population covariance matrix of the observed variables (Σ) is a function of a set of parameters:

$$\Sigma = \Sigma(\theta) = \begin{bmatrix} \text{covariance matrix of y} & \text{covariance matrix of y and x} \\ \text{covariance matrix of x and y} & \text{covariance matrix of x} \end{bmatrix}$$

$$= \begin{bmatrix} (I-\mathrm{B})^{-1}(\Gamma\Phi\Gamma'+\Psi)[(I-\mathrm{B})^{-1}]' & (I-\mathrm{B})^{-1}\Gamma\Phi \\ \Phi\Gamma'[(I-\mathrm{B})^{-1}]' & \Phi \end{bmatrix} \tag{2}$$

where Φ = covariance matrix of x.
Ψ = covariance matrix of ζ.

The matrix $\Sigma(\theta)$ basically consists of three covariance matrices. The unknown parameters $\mathrm{B}, \Gamma, \Phi, \text{and } \Psi$ are simultaneously estimated by finding the parameters such that the covariance matrix ($\hat{\Sigma}$) implied by the model is as close as possible to the sample covariance matrix (S). To know when the estimates are as close as possible, a fitting function that is to be minimized is defined. ML estimation method assuming a multivariate normal distribution was employed for this study. ML estimation was found fairly robust to deviation of multivariate normality and sample size commonly used in transportation research (Golob, 2003). The ML fitting function that is minimized is:

$$F_{ML} = \log|\Sigma(\theta)| + tr(S\Sigma^{-1}(\theta)) - \log|S| - (p+q) \tag{3}$$

The direct effects, which are estimated as $\mathrm{B} \text{ and } \Gamma$, are the influences of one variable on another without the mediation of any intervening variables. The indirect effects are the influences that are mediated by at least one intervening variable. The total effects are the sum of the direct and indirect effects. It should be noted that interpreting a model with the direct effects only provides misleading conclusions when the direct and the total effects are very different. It is the **total effects** that should be used in interpretation. The model building and analysis using SEM parallels the study reported in Kim and Goulias (2003). In additiion, the relationship among all endogecous variables and the variation explained by cross-sectional variables are reported elsewhere Kim and Goulias (2004a). In this paper we focus on the impact chnages have on behavior measured in the year 2000.

The variables reported in Table 7 describe the difference in activity and travel behavior among households and individuals that experienced diametrically opposed events such as increase in employed persons versus a decrease in employed persons, increase in household cars versus a decrease in household cars, as well as personal changes such as change in employment status. As seen in Table 9, in all the events, the effects of personal and household changes on time allocations to activity and travel and the number of activity episodes are not symmetrical and very often are not even in the opposite direction. Consider car ownership change. Persons that experienced either an increase or a decrease in the number of vehicles in the household have on average longer in-home activity duration than the reference group of no change. The travel time, however, reflects the car availability increase and persons spend more time on the road than their counterparts experiencing a decrease in car ownership. Employment changes and children changes as expected explain differences among the participants' behavioural indicators.

Table 7 Total and Direct Effects of Household-level & Person-level Change Variables on Endogenous Variables

Exogenous Variables		Endogenous Variables						
		Hdur	sdur	Nsdur	ttime	finhome	fsub	fnsub
Inadult	Total	-2.837	-0.852	0.165	3.196	0.128	0.011	0.171
	Direct	-0.330	0.000	0.000	0.000	0.128	0.000	0.000
Dnadult	Total	-9.342	-2.697	0.521	11.523	0.189	0.039	0.320
	Direct	0.000	0.000	0.000	6.682	0.189	0.000	0.000
Inkid	Total	-3.686	4.436	-0.857	0.107	0.000	0.008	-0.207
	Direct	0.000	0.000	0.000	0.000	0.000	0.000	-0.206*
Dnkid	Total	-20.819	34.928	-6.751	-7.062	0.000	0.031	-0.084
	Direct	0.303	33.127	0.000	-7.729	0.000	0.000	0.000
Inbaby	Total	-30.287	11.491	32.716	-13.927	-0.246	-0.047	-0.788
	Direct	0.000	0.000	34.937*	-10.403*	-0.246	0.000	-0.456
Dnbaby	Total	5.972	1.524	-0.295	-7.206	0.000	0.087	-0.071
	Direct	0.000	0.000	0.000	-7.732	0.000	0.111*	0.000
Inlicen	Total	-17.644	30.293	-5.855	-6.631	-0.292	0.025	-0.396
	Direct	0.170	28.227	0.000	0.000	-0.292	0.000	0.000
Dnlicen	Total	-23.684	28.505	-5.509	0.685	0.000	0.049	-0.006
	Direct	0.000	28.387	0.000	0.000	0.000	0.000	0.000
Inbpass	Total	12.606	3.217	-0.622	-15.209	0.000	-0.052	-0.150
	Direct	0.000	0.000	0.000	-14.952	0.000	0.000	0.000
Inemp	Total	-1.601	-0.588	0.114	2.076	0.109	-0.101	0.139
	Direct	0.000	0.000	0.000	0.000	0.109	-0.108	0.000
Dnemp	Total	3.032	1.030	-0.199	-3.864	-0.155	-0.013	-0.207
	Direct	0.000	0.000	0.000	0.000	-0.155	0.000	0.000
Inveh	Total	32.075	1.234	-35.273	2.111	0.000	0.024	-0.058

	Direct	0.147	0.000	-35.035	4.606*	0.000	0.000	0.000
Dnveh	Total	21.952	1.889	-19.990	-3.855	-0.096	-0.004	-0.187
	Direct	0.000	0.000	-19.624	0.000	-0.096	0.000	0.000
Expemp	Total	-123.074	188.917	-69.568	3.707	0.000	0.612	-0.514
	Direct	0.000	177.888	-33.055	0.000	0.000	0.276	-0.396
Novemp	Total	-68.121	79.069	-15.282	4.329	0.000	0.554	0.008
	Direct	0.000	79.250	0.000	0.000	0.000	0.408	0.000

Note: A direct effect value of 0.000 for a variable indicates that the variable was constrained to 0 in the model, because of its insignificance at 90% level.
** Significant at 90% level; all others are significant at 95% level.*

Table 8 reports the effects of ICT on time allocations and activity frequencies giving evidence of a lack of symmetry and linearity in the effects when gaining a technology and losing a technology. Although the effects are not exactly symmetrical in most cases, they often have the opposite patterns. For example, new computer users at work spend more time on subsistence and less time on in-home and non-subsistence while past computer users at work have the opposite behaviors in those activities. One interesting fact is, however, that the effects of the past computer users at work are almost symmetrical to those of the experienced computer users, not the new computer users, on in-home, subsistence, and non-subsistence activity durations (i.e., they have different signs but similar coefficients in magnitude). In case of cellular phones, however, the effects of new users and past users are roughly symmetrical on all activity and travel durations.

Table 8 Total and Direct Effects of ICT Variables on Endogenous Variables

Exogenous Variables		Endogenous Variables						
		hdur	sdur	Nsdur	ttime	finhome	fsub	fnsub
Expcw	Total	-43.367	58.044	-11.218	-3.466	-0.193	0.082	-0.517
	Direct	0.000	51.205	0.000	0.000	-0.193	0.000	-0.248
Novcw	Total	-23.632	32.152	-6.214	-2.310	-0.123	0.044	-0.398
	Direct	0.000	26.316	0.000	0.000	-0.123	0.000	-0.228
Quitcw	Total	56.910	-56.452	10.911	-11.368	0.000	-0.336	-0.087
	Direct	0.000	-58.316	0.000	-8.624	0.000	-0.201	0.000
Expnw	Total	-37.708	35.124	-6.789	9.374	0.000	-0.019	0.077
	Direct	0.000	36.766	0.000	8.990	0.000	-0.111	0.000
Novnw	Total	-16.175	19.468	-3.763	0.468	0.000	0.034	0.145
	Direct	0.000	22.569	0.000	0.000	0.000	0.000	0.148*
Expch	Total	-6.138	-1.567	0.303	7.406	0.000	0.025	0.073
	Direct	0.000	0.000	0.000	7.281	0.000	0.000	0.000
Novch	Total	-23.512	14.110	-2.727	12.133	0.000	0.069	0.113
	Direct	0.000	16.523	0.000	11.536	0.000	0.000	0.000
Novnh	Total	6.820	1.741	-0.336	-8.228	0.000	-0.028	-0.081
	Direct	0.000	0.000	0.000	-8.089	0.000	0.000	0.000
Quitnh	Total	-1.307	-0.334	0.065	1.577	0.000	0.272	0.016
	Direct	0.000	0.000	0.000	0.000	0.000	0.266	0.000
Expcel	Total	-46.140	11.381	24.639	10.124	-0.074	0.132	0.073
	Direct	0.000	14.574	26.838	8.980	-0.074	0.085	0.000
Novcel	Total	-21.768	-2.154	17.653	6.273	0.000	0.013	0.100

	Direct	0.000	0.000	17.237	4.922	0.000	0.000	0.000
Quitcel	Total	33.245	3.128	-29.385	-6.992	-0.195	-0.010	-0.346
	Direct	0.000	0.000	-28.781*	0.000	-0.195*	0.000	0.000
Exppag	Total	39.070	-46.488	8.985	-1.118	0.000	-0.080	0.009
	Direct	0.446	-46.295	0.000	0.000	0.000	0.000	0.000
Explap	Total	-71.356	46.193	33.190	-8.034	-0.441	-0.172	-0.486
	Direct	0.000	45.486	42.118*	0.000	-0.441	-0.202	0.000
Novlap	Total	34.995	11.920	-44.073	-2.846	0.000	0.025	-0.556
	Direct	0.000	0.000	-41.769	0.000	0.000	0.000	-0.430
Quitlap	Total	-71.217	-4.425	70.527	5.119	0.000	-0.015	0.206
	Direct	0.000	0.000	69.672	0.000	0.000	0.000	0.000

Note: A direct effect value of 0.000 for a variable indicates that the variable was constrained to 0 in the model, because of its insignificance at 90% level.
** Significant at 90% level; all others are significant at 95% level.*

Experienced and new users of ICT, except for the laptop, generally show a similar pattern in time use and episode frequency by activity. In the case of laptop, the experienced users and new users show quite different effects on all the activity and traveling indicators (different signs or quite different coefficients in magnitude), except for non-subsistence episode frequency.

In the period of 1997-2000, we observed a rapid increase in computer and internet users at home. These two rapidly growing technologies seem to have different effects on people's behavior. The new computer users at home spend less time on in-home activity and more time traveling, while the new Internet users at home spend more time on in-home activity and less time in traveling. In addition, these two groups have the opposite effects on the number of subsistence and non-subsistence episodes.

Using the coefficients in the Tables here we can perform some additional calculations. Regression coefficients defined for a group of indicators are relative to the excluded group (implicitly assumed to have a zero coefficient). Suppose a woman that did not work in 1997 is newly employed in 2000, thus getting a computer and Internet at work, a cell phone, and a laptop. Due to her new employment and ICT use, she spends 139.87 (-0.59+79.07+32.15+19.47-2.15+11.92) minutes more on subsistence activity than her previous status, resulting from an increase in the number of employed persons in the household (-0.589 in Table 9), new employment (79.069 in Table 9), starting using a computer and Internet at work (32.15 and 19.47 in Table 10, respectively), starting using a cellular phone (-2.15 in Table 10), and starting using a laptop (11.92 in Table 10). Similarly, it turns out that she spends 96.30 minutes less on in-home activity, 51.57 minutes less on non-subsistence activity, and 7.99 minutes more on travel than others. Again, the sum of changes in time allocation is equal to zero (139.87-96.30-51.57+7.99=0) showing how the time reallocation (trade-off among activities and travel) occurs with a limited time budget after her employment. Similar calculations applied to the number of activity episodes lead to 0.57 more subsistence episodes and 0.56 less non-subsistence episodes than her previous status. In addition, men spend on average 34.35 minutes less on in-home activity, 32.32 minutes more on subsistence activity, 6.25 minutes less on non-subsistence activity, and 8.28 minutes on travel, and have 0.08 more subsistence episodes and 0.20 less non-subsistence episodes than women. These are not negligible differences.

Dependence on Past Behavior

In order to account for habit persistence effects we first derive using latent class cluster analysis a set of relatively homogenous groups of activity participation behavior in 1997. The following clustering variables are used:

- Total in-home activity duration in day1 and day2 (Hdur1, Hdur2)
- Total out-of-home subsistence activity duration in day1 and day2 (Sdur1, Sdur2)
- Total out-of-home non-subsistence activity duration in day1 and day2 (Nsdur1, Nsdur2)
- Total travel time in day1 and day2 (Ttime1, Ttime2)
- Number of in-home activity episodes in day1 and day2 (Finhome1, Finhome2)
- Number of in-home activity episodes in day1 and day2 (Fsub1, Fsub2)
- Number of out-of-home non-subsistence activity episodes in day1 and day2 (Fnsub1, Fnsub2)

Starting from a one-cluster model we build in a sequence models with more clusters until the cluster sizes become too small to be meaningful and the difference in goodness of fit between successive models is not significant. Table 9 shows the seven types of activity–travel behavior and their average profiles showing wide variability in time allocation and frequency of activity episodes among clusters. The first and largest cluster contains 23.9% of the sample appears to be the non-workers cluster. This group has the second longest time at home (22-22.5 hours per day), no subsistence activity time, and a high frequency of non-subsistence activity episodes in both days. The second, third, and fourth clusters appear to be regular workers/students clusters with 21.1%, 17.01%, and 13.6% of the sample, respectively. Although all these groups have a consistent activity-travel pattern between the two days, they have different levels of activity participation patterns. The second cluster (worker_a) and the fourth cluster (worker_c) show two different ends of activity-travel behavior for regular workers/ students, the third cluster (worker_b) is the “middle” between these two behaviors. In other words, among the three groups, worker_a group has the shortest time in subsistence activity but the longest time in non-subsistence activity and traveling in both days. This group is also characterized by high frequency of episodes in all activity types. On the other hand, worker_c group has the longest time in subsistence activity and in-home activity but the shortest time in non-subsistence activity and traveling. Worker_c group is characterized by low frequency of all activity episodes. The sixth cluster (hbound) with 7.2% of the sample is characterized by their home bound activity behavior in both days. This group spends the majority of time on in-home activity and a very short time on out-of-home activity and traveling. The other clusters (pwork_a and pwork_b) have different time use patterns in in-home and subsistence activity between the two days.

Table 9 Average Profile of Activity and Travel Clusters

	Variables used to create clusters	Cluster1 (Nworker)	Cluster2 (Worker_a)	Cluster3 (Worker_b)	Cluster4 (Worker_c)	Cluster5 (Pwork_a)	Cluster6 (Hbound)	Cluster7 (Pwork_b)
	Cluster Size (%)	23.92	21.14	17.01	13.75	10.18	7.19	6.80
Day 1	Hdur1(min.)	1259.59	792.71	775.61	799.82	812.93	1305.55	1143.11
	Sdur1 (min.)	0.00	443.10	524.33	564.53	240.05	0.00	0.28
	Nsdur1 (min.)	120.17	91.32	49.66	1.48	280.93	91.69	191.07
	Ttime1 (min.)	60.23	112.87	90.40	74.17	106.09	42.76	105.53
	Finhome1	2.49	2.69	2.49	2.08	2.46	1.84	2.57
	Fsub1	0.00	1.91	1.62	1.36	1.12	0.00	0.01
	Fnsub1	2.78	2.24	1.81	0.27	2.67	1.94	3.82
Day 2	Hdur2 (min.)	1227.70	783.03	794.91	810.57	1021.12	1439.73	957.30
	Sdur2 (min.)	0.03	417.69	523.41	555.88	0.03	0.00	296.25
	Nsdur2 (min.)	142.08	123.76	38.24	1.01	337.86	0.19	102.03
	Ttime2 (min.)	70.20	115.52	83.44	72.54	80.98	0.07	84.42
	Finhome2	2.57	2.68	2.42	2.06	2.32	1.02	2.60
	Fsub2	0.00	1.74	1.63	1.37	0.01	0.00	1.33
	Fnsub2	2.99	2.41	1.62	0.26	3.11	0.02	2.24
Number of cases: 1480					BIC (based on LL): 160289.54			
Number of parameters (Npar): 226					AIC (based on LL): 159091.78			
Log-likelihood (LL): -79319.89					CAIC (based on LL): 160515.54			

Each cluster is assigned a dummy indicator for cluster membership and then entered as explanatory variable in the SEM. Turning to the effects of these clusters on year 2000 behavior and summarized in Table 10, each group has almost identical patterns of time use and activity frequency to those in the year 1997 (Table 9) derived from the LC cluster analysis. For example, the home-bound group (Hbound) spends more time on in-home and less time on non-subsistence and traveling than any other group. Additionally, this group has the lowest number of activity episodes in all activity types. Among "regular" worker groups (worker_a, worker_b, and worker_c) worker_c group spends the most time on subsistence and the least time on in-home, non-subsistence, and traveling, and it has the least activity episodes in all activity types. On the other hand, worker_a group has the exact opposite position, except for in-home duration. In other words, this group spends the least time on subsistence and the most time on non-subsistence and traveling among the three groups, and it has the most activity episodes in all activity types. The time use and activity frequency of worker_b group are in the middle of worker_a and worker_c, except for a little less time on in-home than both worker_a and worker_c . Figures 3 and 4 provide a better pictorial comparison of time use and activity frequency patterns. These identical patterns of activity and travel behavior among the groups over the 3 year period of 1997-2000, confirm people's strong habit persistence in activity and travel behavior.

Table 10 Total and Direct Effects of Previous Activity and Travel Patterns on Endogenous Variables

Exogenous Variables	Endogenous Variables

		hdur	sdur	Nsdur	ttime	finhome	fsub	Fnsub
Hbound	Total	28.876	9.401	-24.783	-13.502	-0.477	-0.026	-0.928
	Direct	0.000	0.000	-22.966*	0.000	-0.477	0.000	-0.221
worker_a	Total	-80.633	51.461	14.761	14.413	0.000	0.361	-0.022
	Direct	0.000	50.989	24.707	9.723	0.000	0.232	-0.196
worker_b	Total	-69.917	86.376	-16.694	0.227	-0.115	0.316	-0.160
	Direct	0.000	85.474	0.000	0.000	-0.115	0.174	0.000
worker_c	Total	-82.066	104.559	-20.209	-2.296	-0.191	0.162	-0.726
	Direct	0.000	93.186	0.000	0.000	-0.191	0.000	-0.451
pwork_a	Total	-58.759	21.470	35.449	1.839	-0.091	0.134	-0.003
	Direct	0.000	23.417	39.599	0.000	-0.091*	0.107	0.000

Note: A direct effect value of 0.000 for a variable indicates that the variable was constrained to 0 in the model, because of its insignificance at 90% level.
** Significant at 90% level; all others are significant at 95% level.*

SUMMARY AND CONCLUSIONS

In this paper, using panel survey data and structural equations models complex relationships among the activity and travel indicators were studied by incorporating indicators of change in time. The system of equations defined here includes as dependent variables the amount of time allocated to in-home, out-of-home subsistence, out-of-home non-subsistence, and travel, as well as the total number of episodes by activity type. In order to get a clear trade-off relationship in time use among different activities and travel within a limited 24-hour time budget, in-home duration is extracted and included in the model system. This allows us to take into account a fixed time budget explicitly in the models and detect the existence of very strong substitutional and complementary relationships in time use among different activities and travel. It also enables us to uncover how persons are different in allocating their time when they experience a change in their life and they need to change their activity and travel behavior. The changes we study are changes in socioeconomic, demographic, and technology ownership and availability. Out-of-home activity (subsistence and non-subsistence) duration and travel time have very large substitutional effects (-0.834 to -1.022) on in-home activity duration, while out-of-home activity duration has complementary effects on travel time (0.024 to 0.074).

Using information on changes in social and economic circumstances between 1997 and 2000 a number of change variables are defined and included in the model as explanatory variables to test the existence of behavioral symmetry when opposite events take place. In the majority of change effects we found social and economic changes to be non symmetric in influencing activity and travel behavior. In addition, the effects of different levels of ICT ownership and use on activity and travel behavior are also examined jointly with all the other determinants of activity and travel behavior. The overall "technology" effect seems to depend on the location and type of technology. It is also found that the technology effects are differentiated depending on the levels of ICT ownership and use.

Through latent class clustering analysis, seven homogenous groups in activity engagement and time use are first identified, and then the group indicators are included as explanatory variables in the model system. This method allows us to test if there is any habit persistence of individuals in activity and travel behavior, and at the same time, avoid many problems resulting from strong serial correlation in panel data. The model results confirm the existence of strong habit persistence in activity engagement and time use even in a relatively long period of time (3 years).

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